



“Enhancing California’s Water Resources Management and Decision Support System Through Remote Sensing of Precipitation”

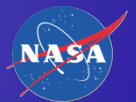
Soroosh Sorooshian

Center for Hydrometeorology and Remote Sensing

University of California Irvine



*NASA and DWR Remote Sensing and
drought Monitoring and Response Workshop
Sacramento CA: Feb. 25th 2014*

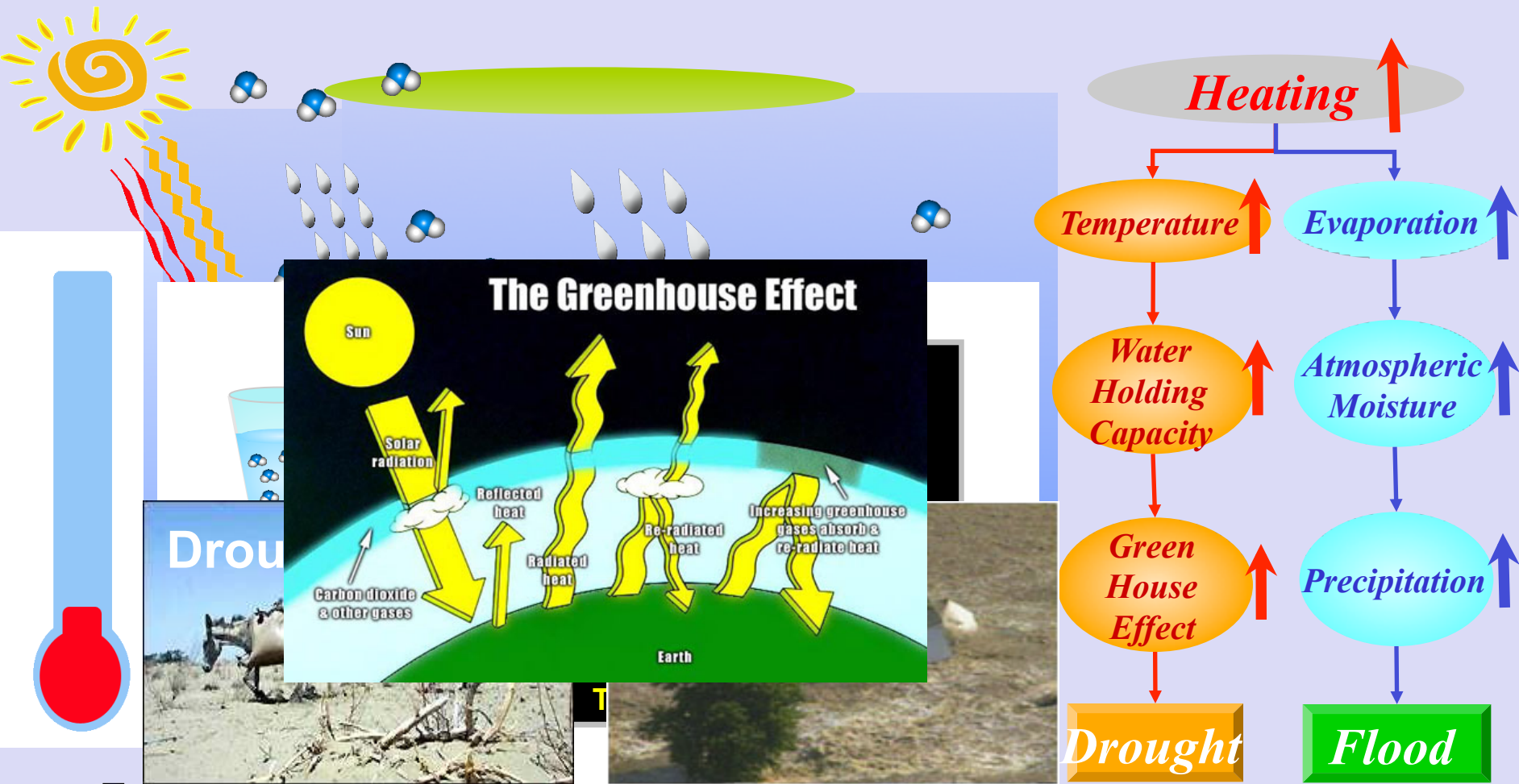


University of California Presenters (Ad Ent) Past



and many more ...

Global Warming And Hydrologic Cycle Connection

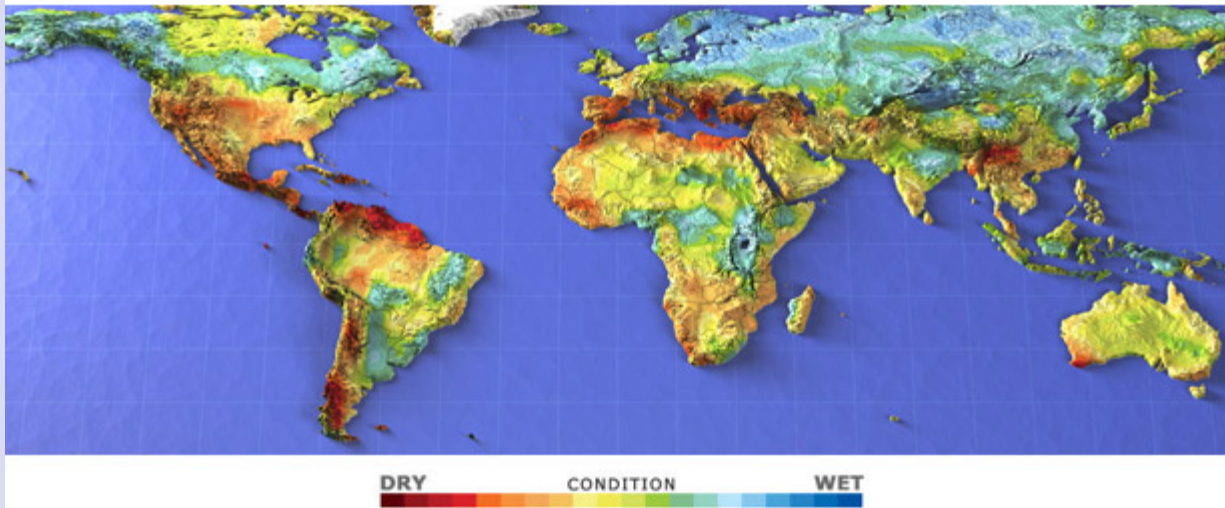


Created by: Gi-Hyeon Park

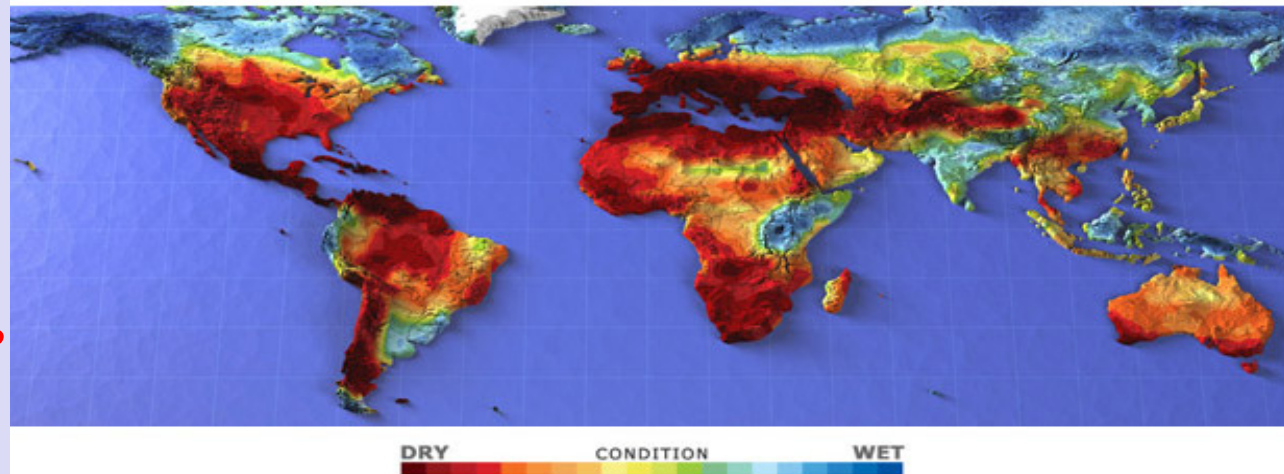
Center for Hydrometeorology and Remote Sensing, University of California, Irvine

Global Climate: Past Decade and Prediction of End of 21st Century

2000-2009



2090-2099



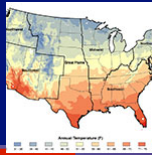
Fair Question:

*Where does all the
additional Precipitation go?*



Regional Climate Trends and Scenarios: The Southwest U.S.

USGCRP July 30, 2013



Precipitation

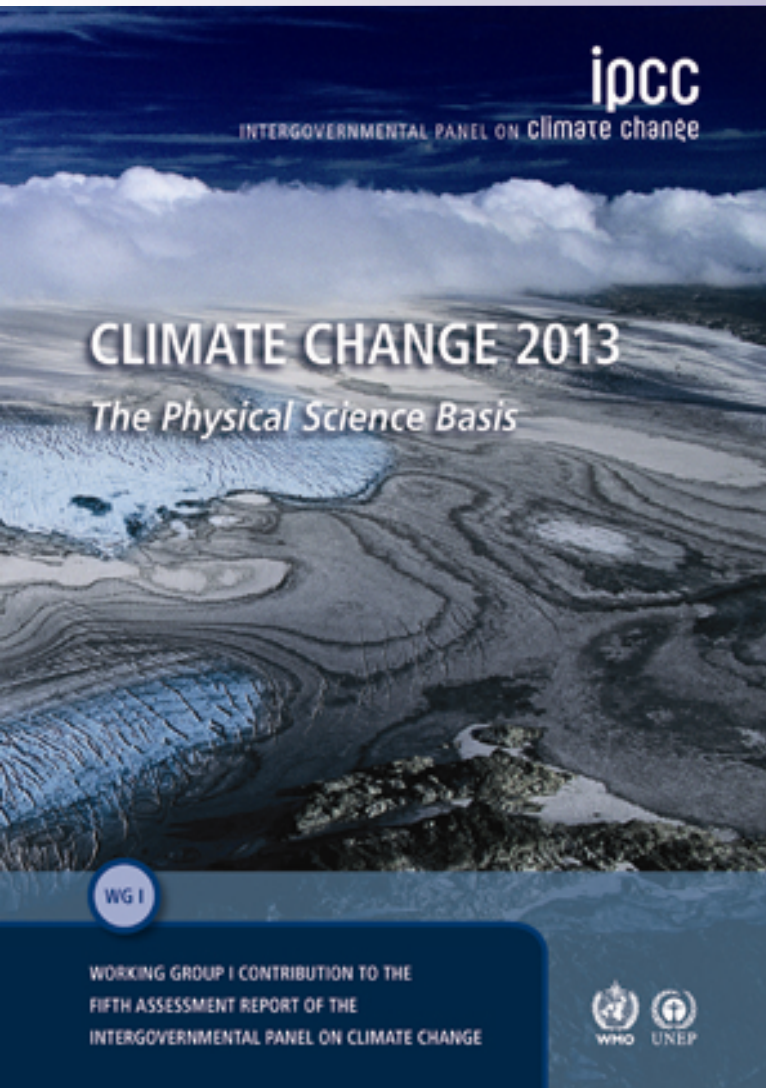
- *“Precipitation does not exhibit any obvious long-term trends for the Southwest U.S., except for Fall, which shows a slight upward trend. Trends are not statistically significant for any season.*
- *The region experienced its wettest conditions in the 1980s and 1990s (coinciding with a shift in Pacific climate in 1976, after which El Niño became much more frequent), but has dried in the last decade.*

Extremes

- *There is not a statistically significant trend in the occurrence of extreme precipitation events in the Southwest.”*



Recently Released IPCC Report (AR5) - Sept. 2013



- *“It is likely that since 1950 the number of heavy precipitation events over land has increased in more regions than it has decreased.”*
- *“..... there continues to be a lack of evidence and thus low confidence regarding the sign of trend in the magnitude and/or frequency of floods on a global scale”*



A Key Requirement!



*Precipitation Measurement is one of
the KEY
hydrometeorologic Challenges*

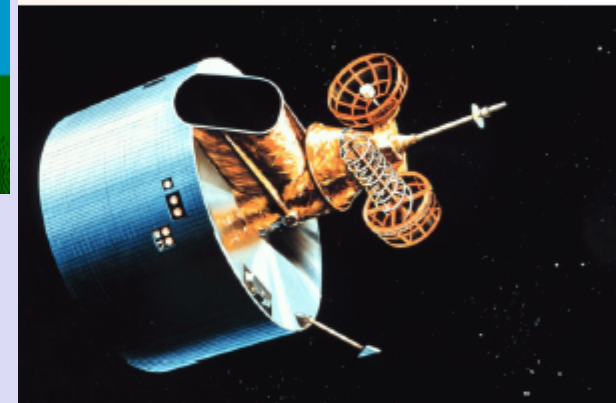
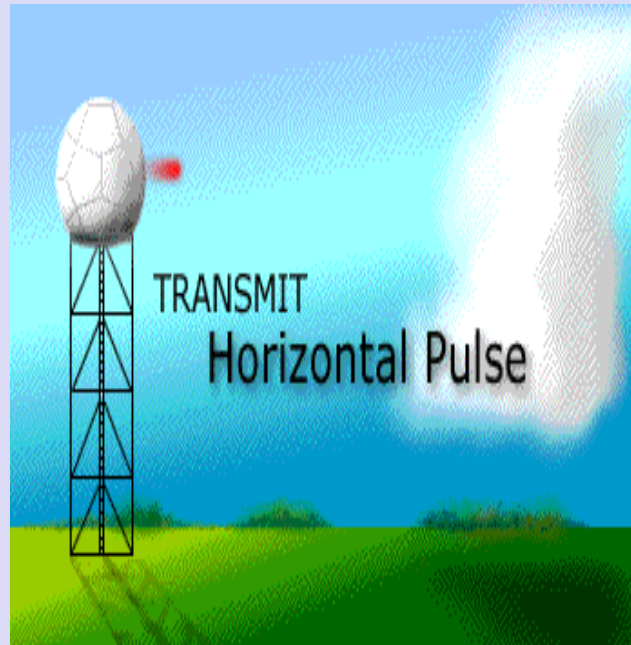
*Push towards High Resolution (Spatial and Temporal) Global
Observations and Modeling*



Precipitation Observations: Which to trust??



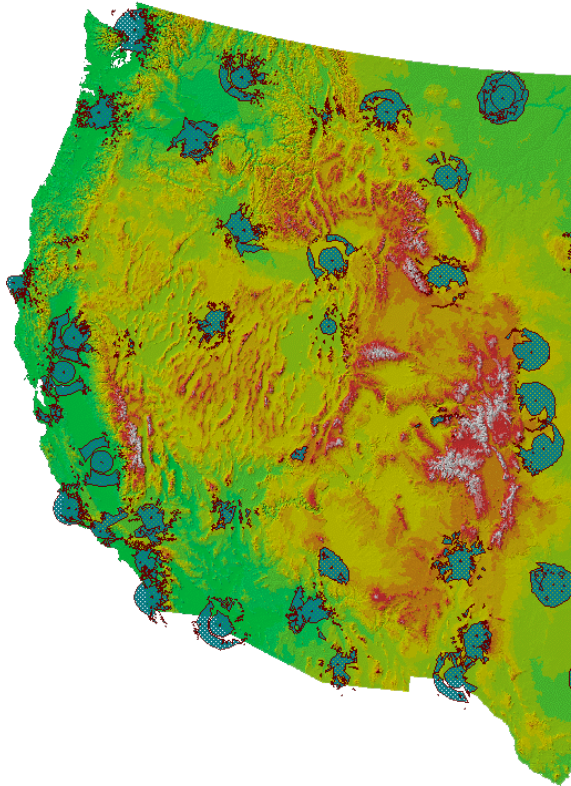
Rain Gauges



Satellite

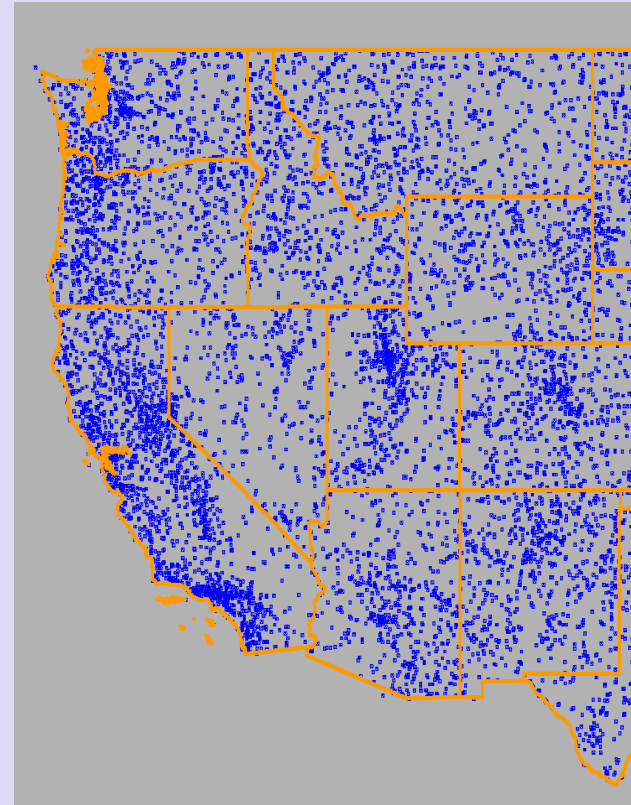


Coverage of the WSR-88D and gauge networks



1 km AGL

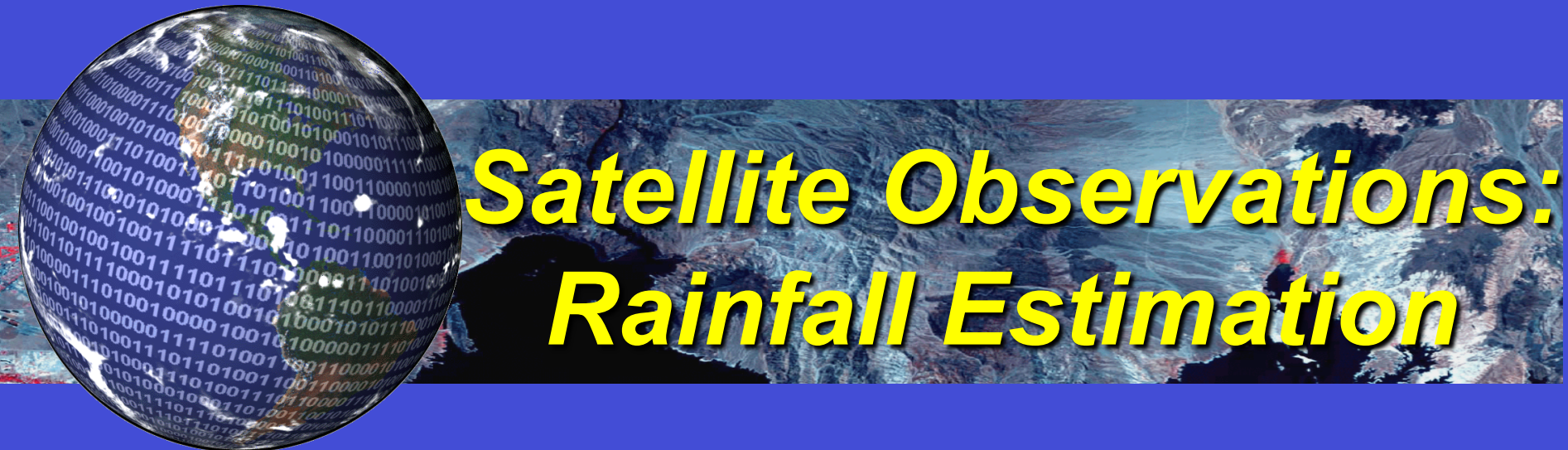
Maddox, et al., 2002



*Daily precipitation
gages (1 station per 600 km²
for Colorado River basin)
hourly coverage
even more sparse*



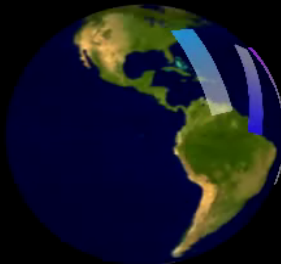
Space-Based Observations



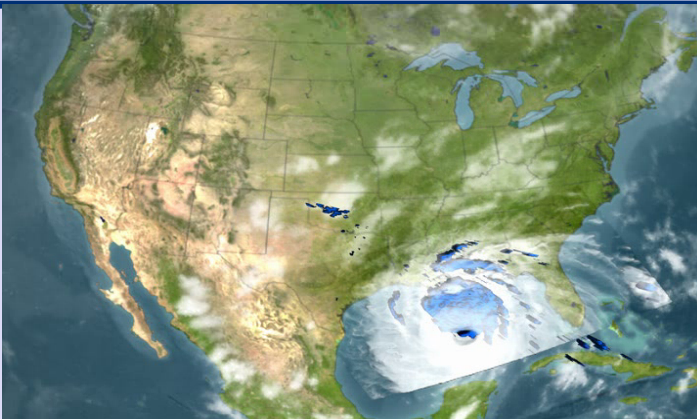
Satellite Data for Precipitation estimation



*Geostationary IR
Cloud top data
15-30 minute temporal
resolution*



*Passive Microwave (SSM/I)
Some characterisation of rainfall
~2 overpasses per day per
spacecraft, moving to 3-hour return time
(GPM)*



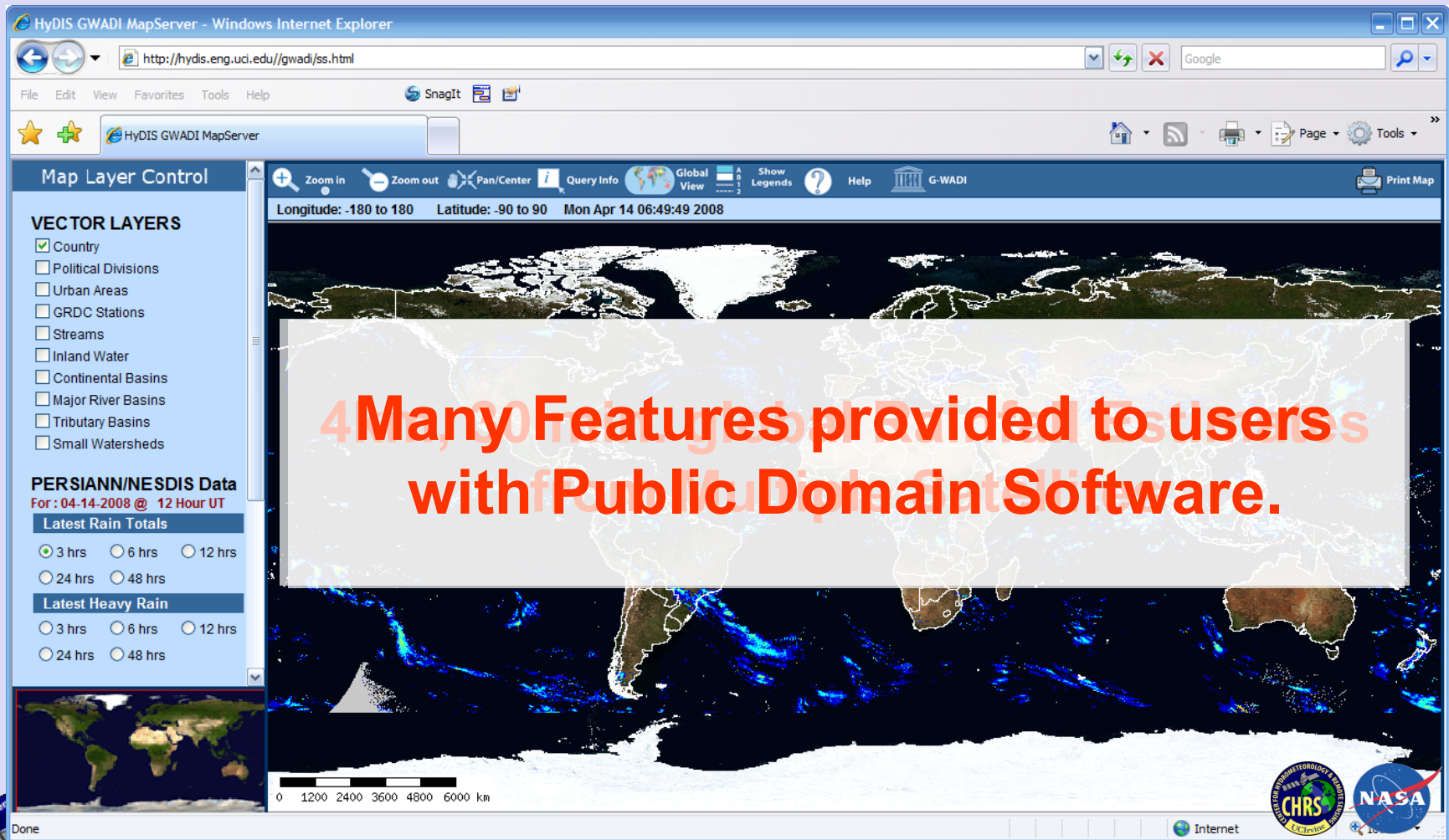
*TRMM precipitation RADAR
3D imaging of rainfall
1-2 days between overpasses
(S-35°N-35 °)*



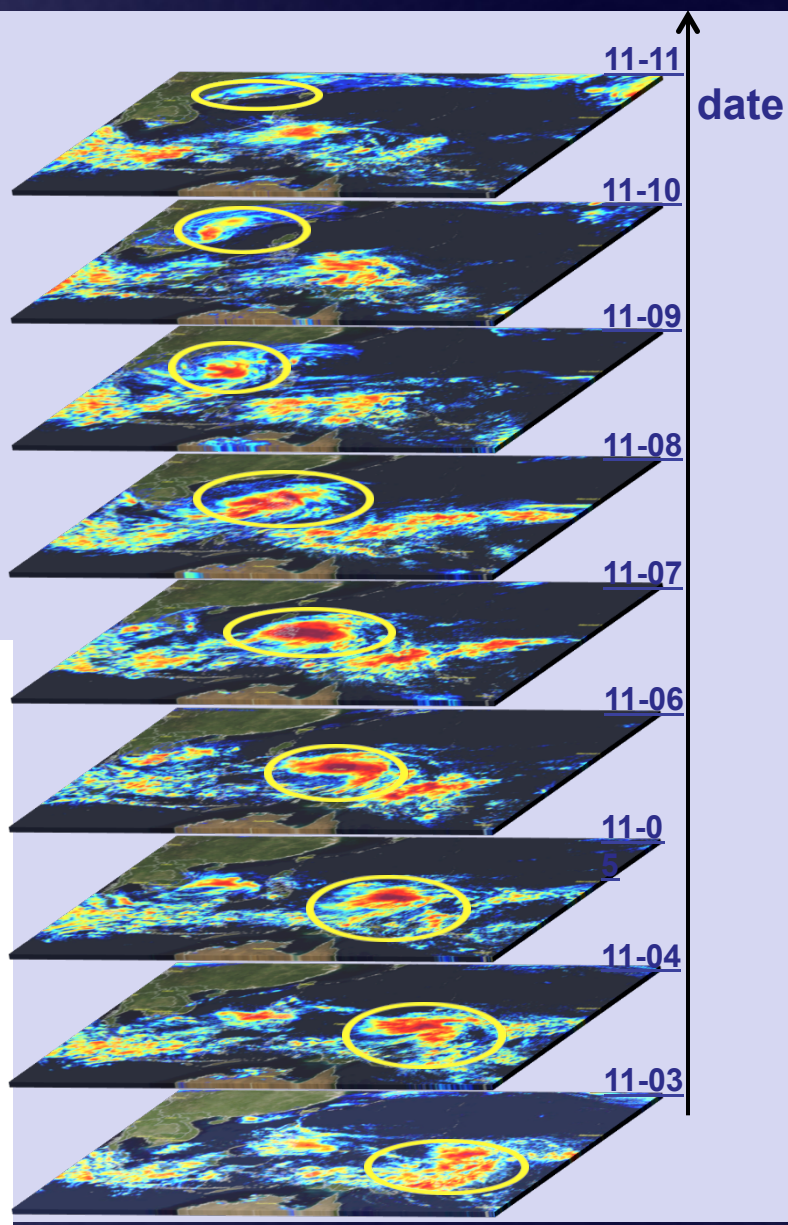
Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)



Real Time Global Data: Cooperation With UNESCO



Daily precipitation (mm/day) of Typhoon Haiyan

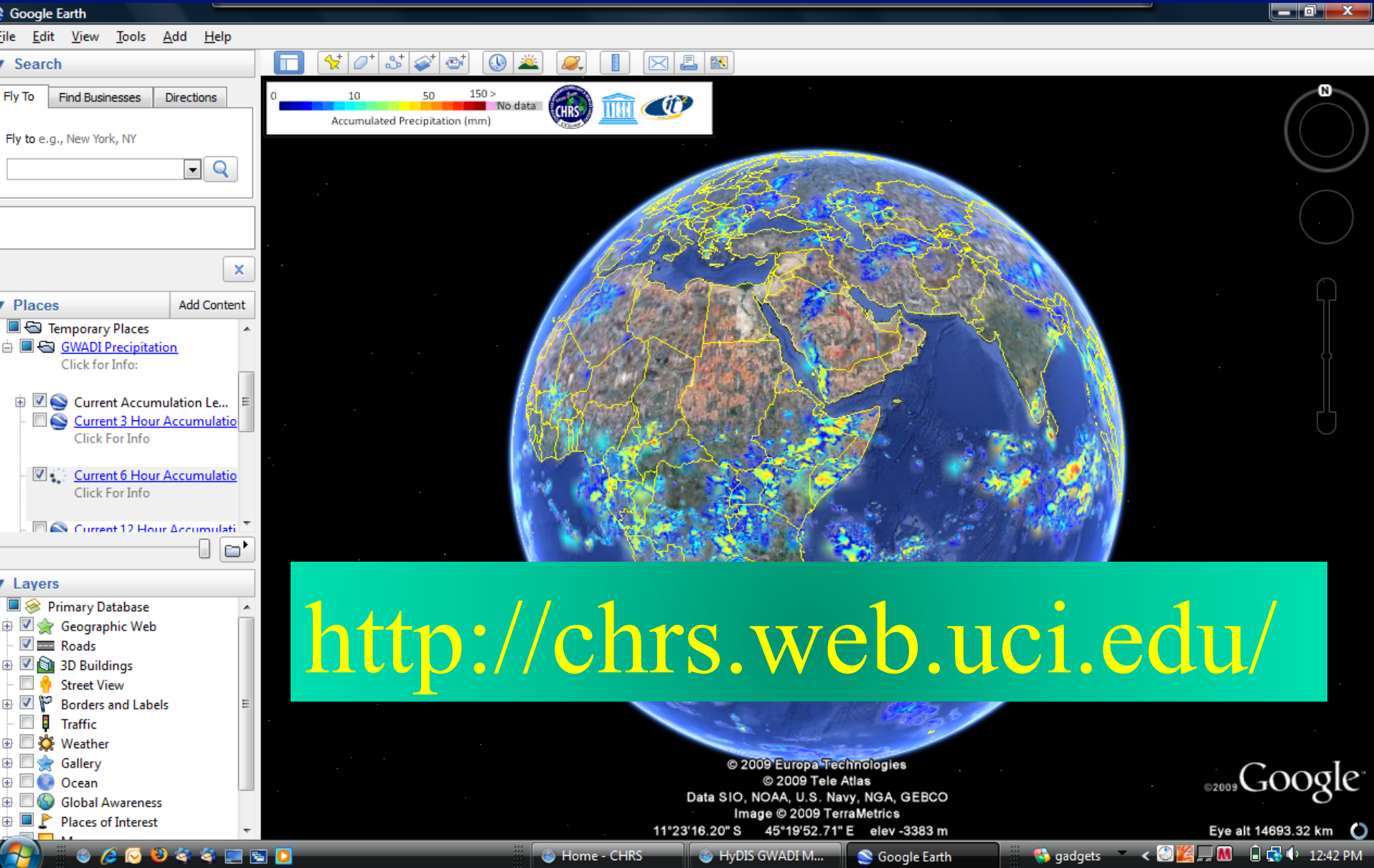


Tracking characteristics of Typhoon Haiyan

Date	Max Precip. Intensity (mm/d)	Total Volume (km3)
11/3/2013	243.67	143.254
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11/10/2013	130.69	24.673
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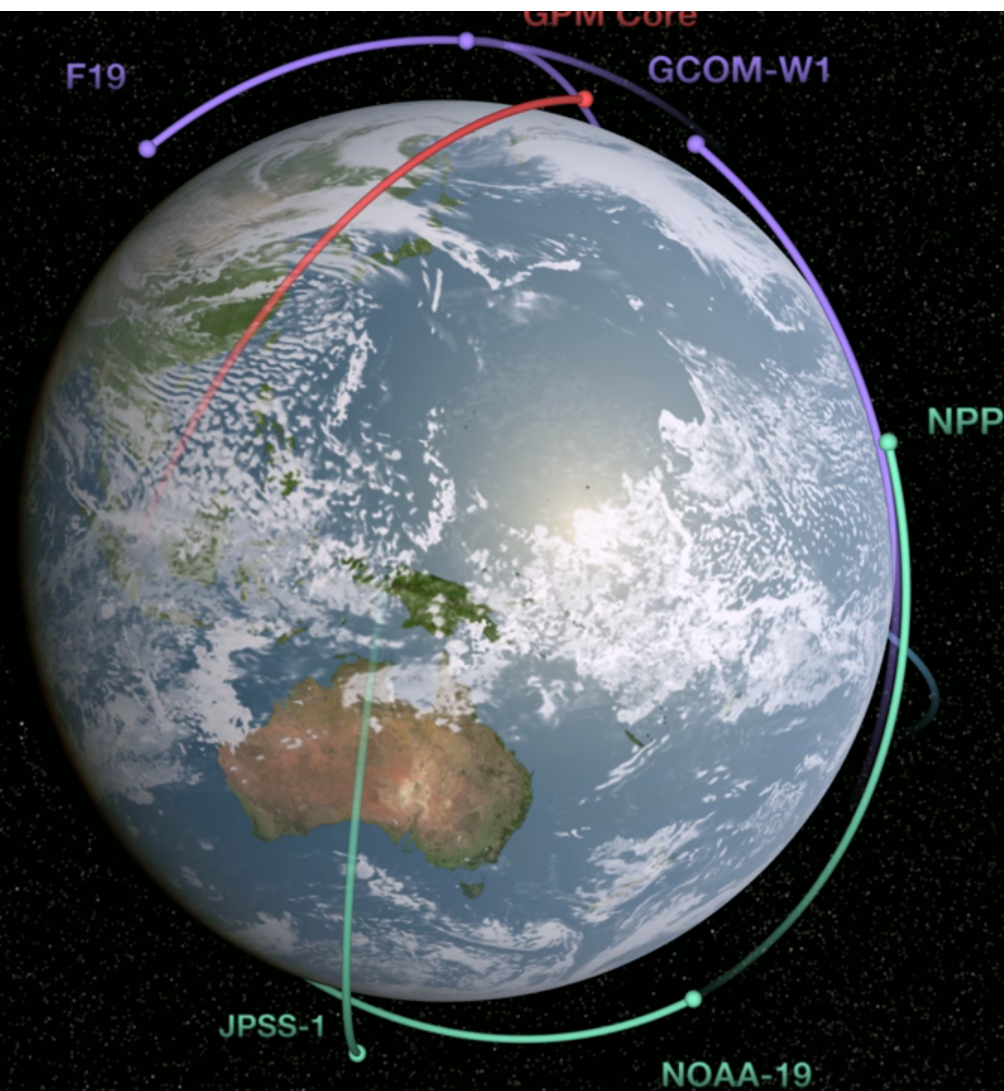


PERSIANN Satellite Product On Google Earth



GPM Animation

Courtesy: NASA's ESE





Validation and Application of Satellite Products



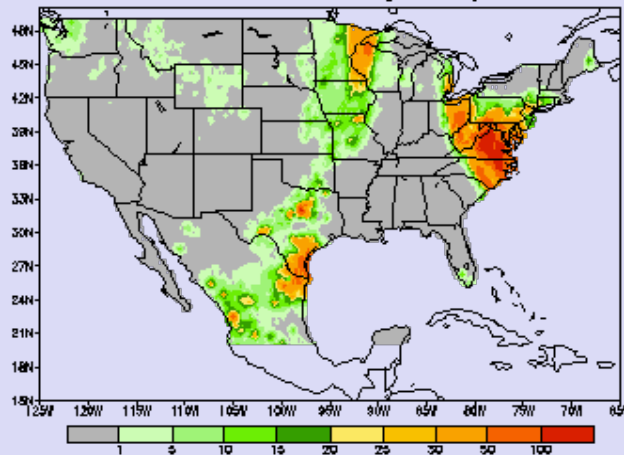
Center for Hydrometeorology and Remote Sensing, University of California, Irvine

US Daily Precipitation Validation Page

http://www.cpc.ncep.noaa.gov/products/janowiak/us_web.html

13Z 19Sep2003 thru 12Z 19Sep2003
Data on 0.25 deg grid (UNITS are mm/day)

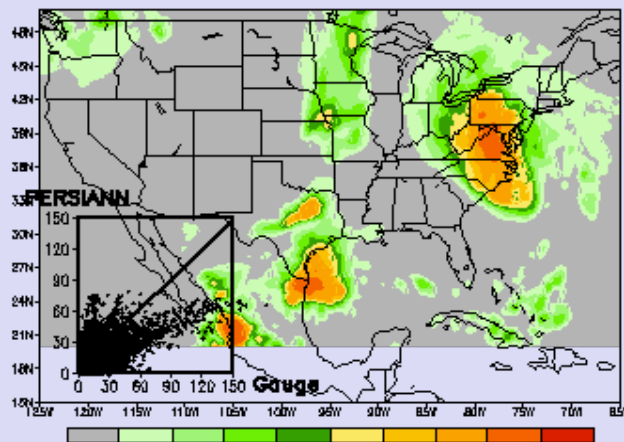
CPC real-time Gauge Analysis



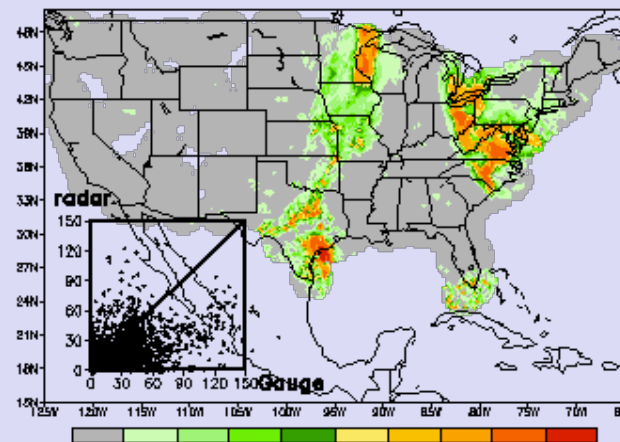
	(G) gauge	(S) PERSIANN	(R) radar
Number of points:	13828.	13828.	13828.
# points w/rain:	4249.	4665.	2971.
Mean rain rate:	5.55	4.25	3.13
Cond. rain rate:	17.82	12.47	14.46
Max. rain rate:	181.99	79.07	131.45
Correlation:	G-S 0.827	G-R 0.726	R-S 0.606
Mean Absolute Error:	3.63	3.42	3.35
RMSE (mm/day):	9.44	11.23	8.66
RMSE (normalized):	1.70	2.02	2.77
Probability of Detection:	0.746	0.654	0.855
False Alarm Ratio:	0.321	0.065	0.455
Bias Ratio (rain:no rain):	1.096	0.699	1.570
Heidke Skill Score:	0.574	0.692	0.546
Hanssen-Kuipers Score:	0.589	0.634	0.660
Equitable Threat Score:	0.402	0.528	0.376

	PERSIANN			radar	
	< 1	≥ 1		< 1	≥ 1
< 1 gauge	8082.	1497.	< 1 gauge	9386.	193.
≥ 1 gauge	1081.	3168.	≥ 1 gauge	1471.	2778.

PERSIANN



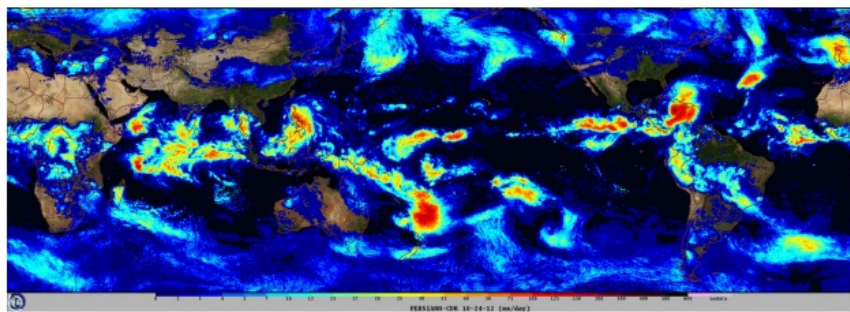
Radar



NOAA's Climate Data Record (CDR) Program

PRECIPITATION ESTIMATION FROM REMOTE SENSING
INFORMATION USING ARTIFICIAL NEURAL NETWORK

PERSIANN



PERSIANN CLIMATE DATA RECORD SPECIFICATIONS

- 0.25-deg * 0.25-deg (60°S–60°N latitude and 0°–360° longitude)
- Daily Product
- 1980–present
- Updated Monthly

INPUTS TO THE PERSIANN CLIMATE DATA RECORD

- GridSat-B1 CDR (IRWIN)
- GPCP 2.5-deg Monthly Data

SOME USES OF THE PERSIANN CLIMATE DATA RECORD

- Climatologists can perform long-term climate studies at a finer resolution than previously possible.
- Hydrologists can use PERSIANN-CDR for rainfall-runoff modeling in regional and global scale, particularly in remote regions.
- Performing extreme Event Analysis (intensity, frequencies, and duration of floods and droughts).
- Water Resources Systems Planning and Management

PERSIANN CLIMATE DATA RECORD

<http://www.ncdc.noaa.gov/cdr/operationalcdrs.html>

CLIMATE DATA RECORD PROGRAM INFORMATION

<http://www.ncdc.noaa.gov/cdr/index.html>



NO

Home Operational CDR

CLIMATE DATA

► Serving the Public

► Data

► Development Guidelines

► Contact Us

News

[Congratulations Cheng-Zhi](#)

[2013 CDR Annual Meetings
Presentations now available](#)



SEARCH
NCDC

Environmental Satellites: Interim
ated. The first step in establishing
e dataset itself, and supporting
opers Guidelines.

Atmospheric, Oceanic, and
temperatures) that have been improved
DRs are geophysical variables
specific to various disciplines.
output.

Source de	Documentation
	Algorithm Description Data Flow Diagram Maturity Matrix
	Algorithm Description Data Flow Diagram Maturity Matrix
	Algorithm Description Data Flow Diagram Maturity Matrix
	Algorithm Description Data Flow Diagram Maturity Matrix
	Algorithm Description Data Flow Diagram Maturity Matrix



Center for



www.climate.gov
www.ncdc.noaa.gov

Protecting the past... Revealing the future

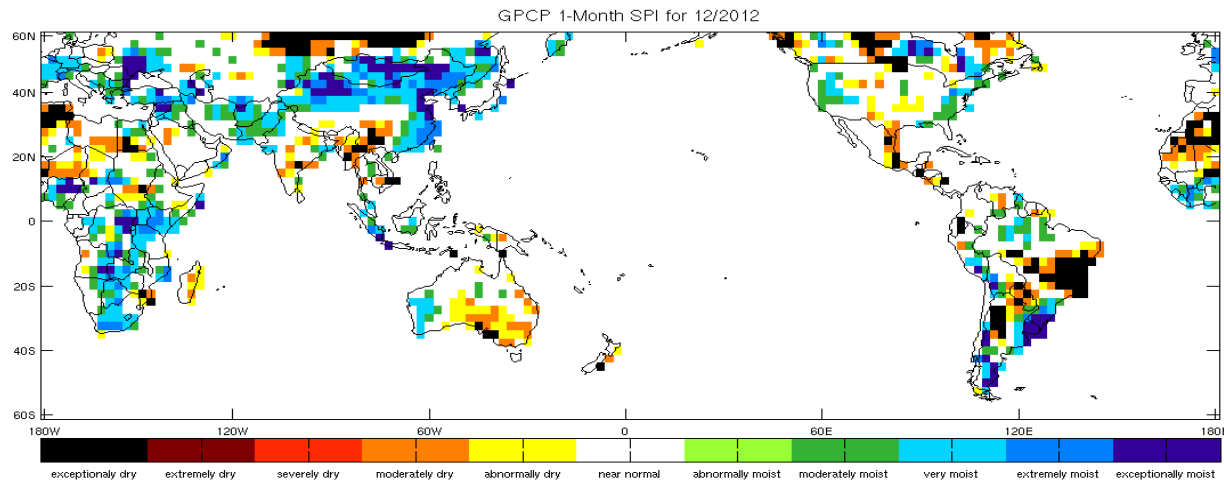
September 2013

Global Drought Monitoring

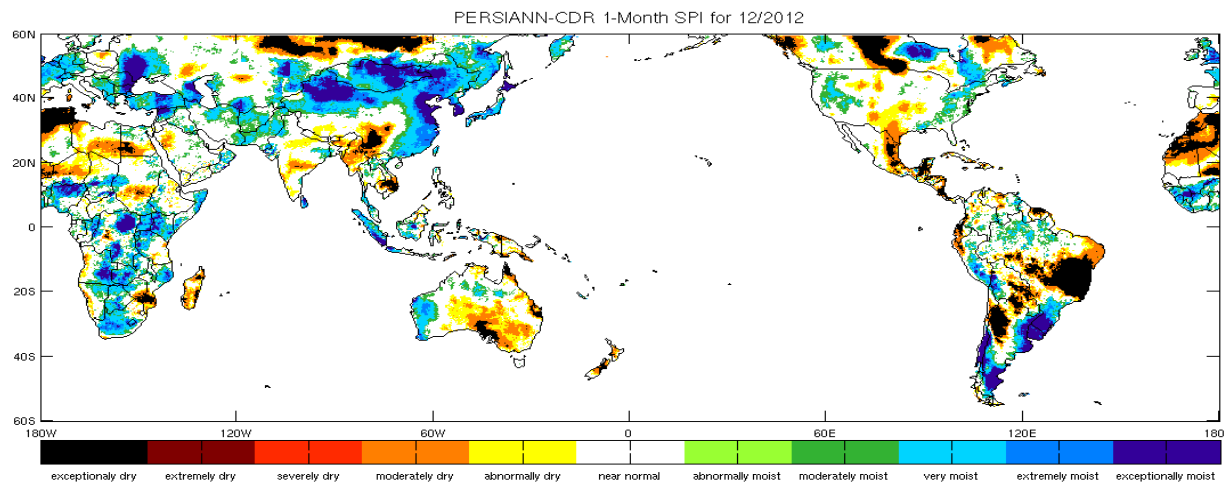


Monitoring global “abnormal” wetness and dryness conditions using Standard Precipitation Index (SPI) method from GPCP 2.5-deg monthly (top) and PERSIANN-CDR 0.25-deg daily (bottom) for the period of 1983-2012. NOTICE the difference in spatial resolution

GPCP 2.5-deg monthly



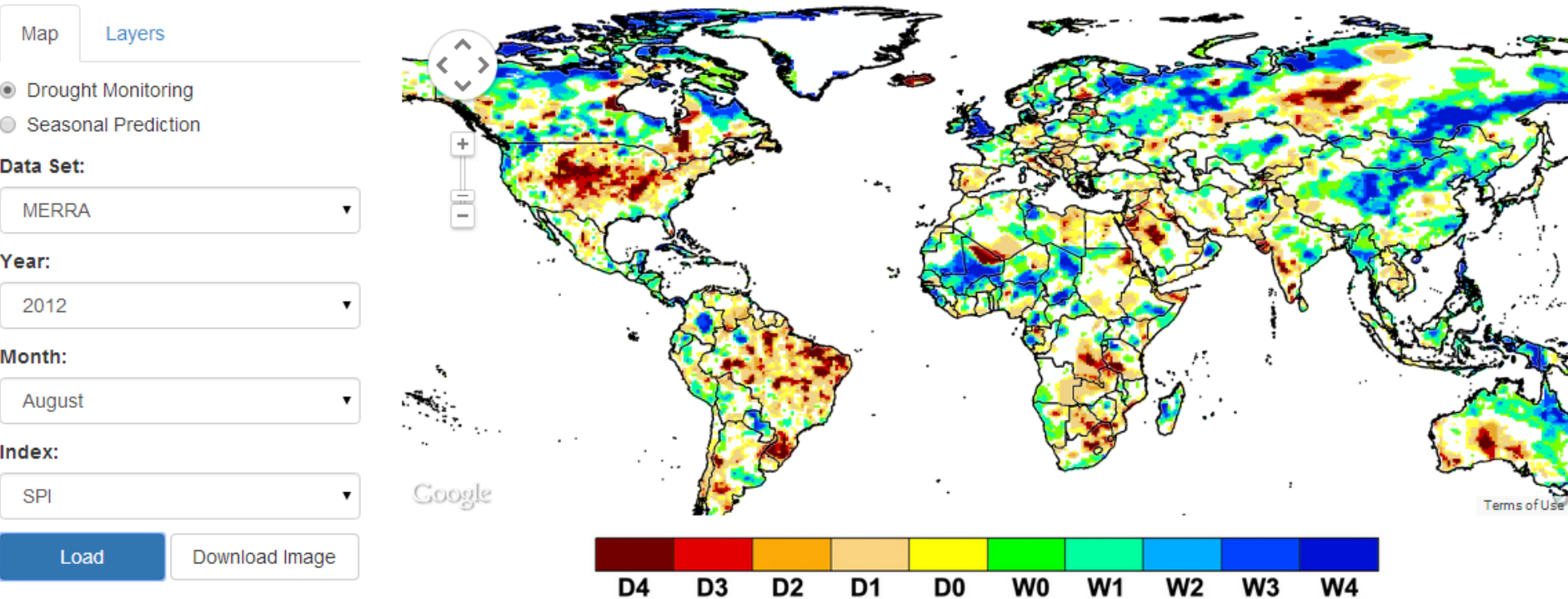
PERSIANN-CDR 0.25-deg daily



H. Ashouri

UC-I Global Drought Monitoring System

Global Integrated Drought Monitoring and Prediction System (GIDMaPS)



<http://drought.eng.uci.edu/>

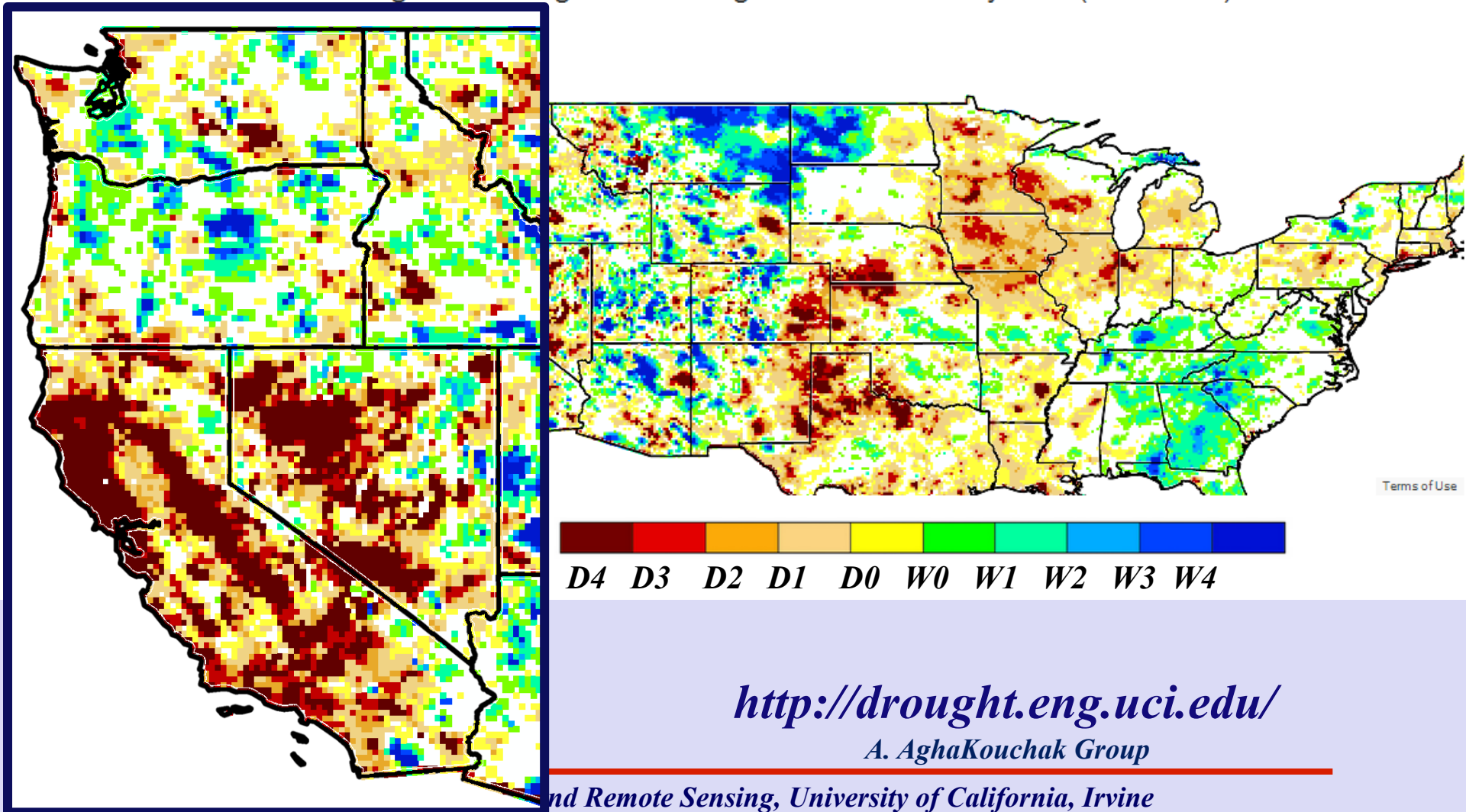
A. AghaKouchak Group



Center for Hydrometeorology and Remote Sensing, University of California, Irvine

UC-I Global Drought Monitoring System

Global Integrated Drought Monitoring and Prediction System (GIDMaPS)



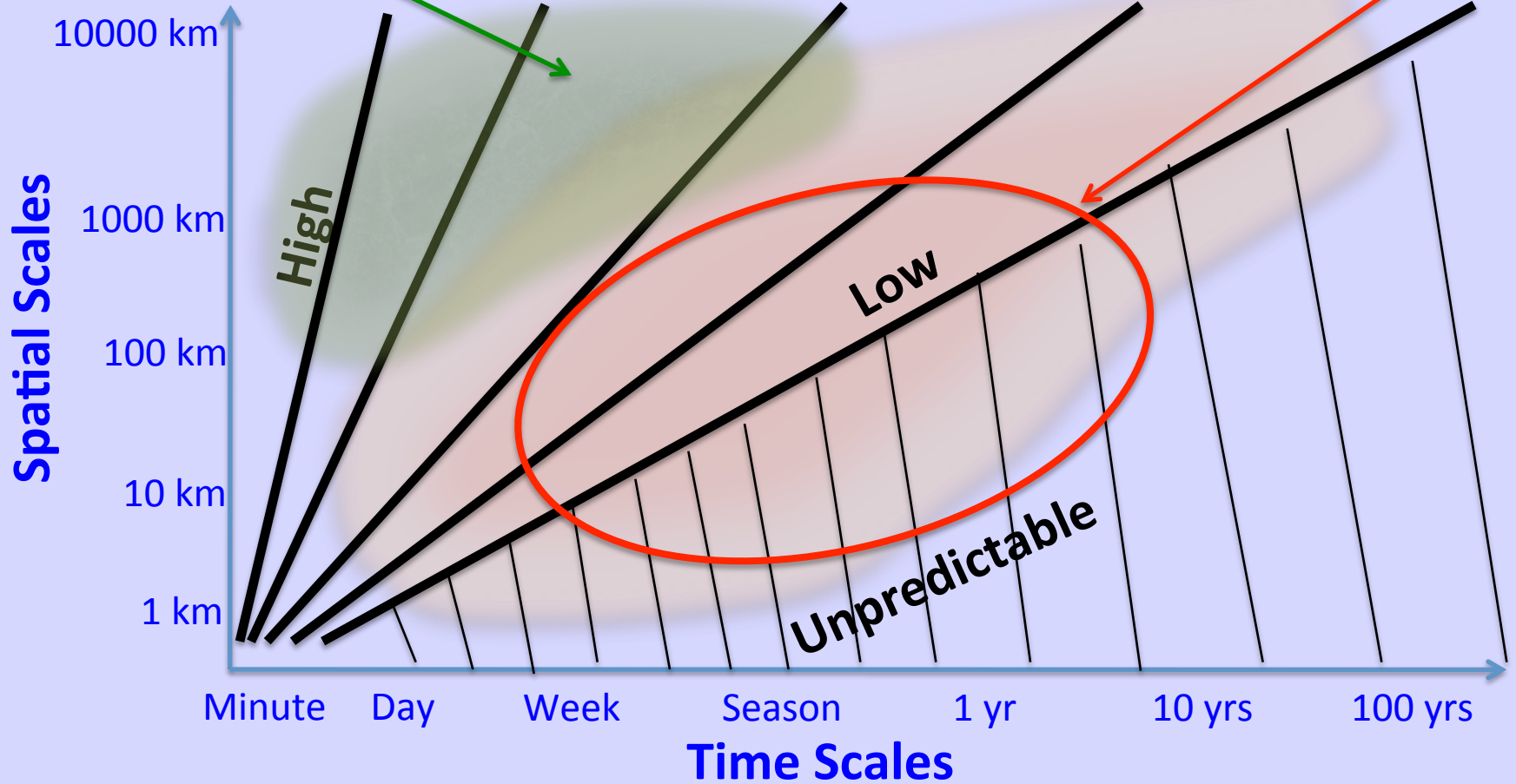
What Do Models Tell Us About Future Precipitation Patterns and Amounts?



Drought Predictability

Current Skill

User Needs



Recent Evaluation of RCM/GCM over Western U.S.

Wei Chu 2011

Current period: 1971-2000

Future period: 2041-2070

Spatial Res.: 50 km

Temporal Res.: daily

Regional Models	Climate Models			
	GFDL	CGCM3	HADCM3	CCSM
CRCM				
ECP2				
HRM3				
MM5I				
RCM3				
WRFG				



Outputs of six RCM/GCM sets:

North American Regional Climate Change
Assessment Program (NARCCAP)

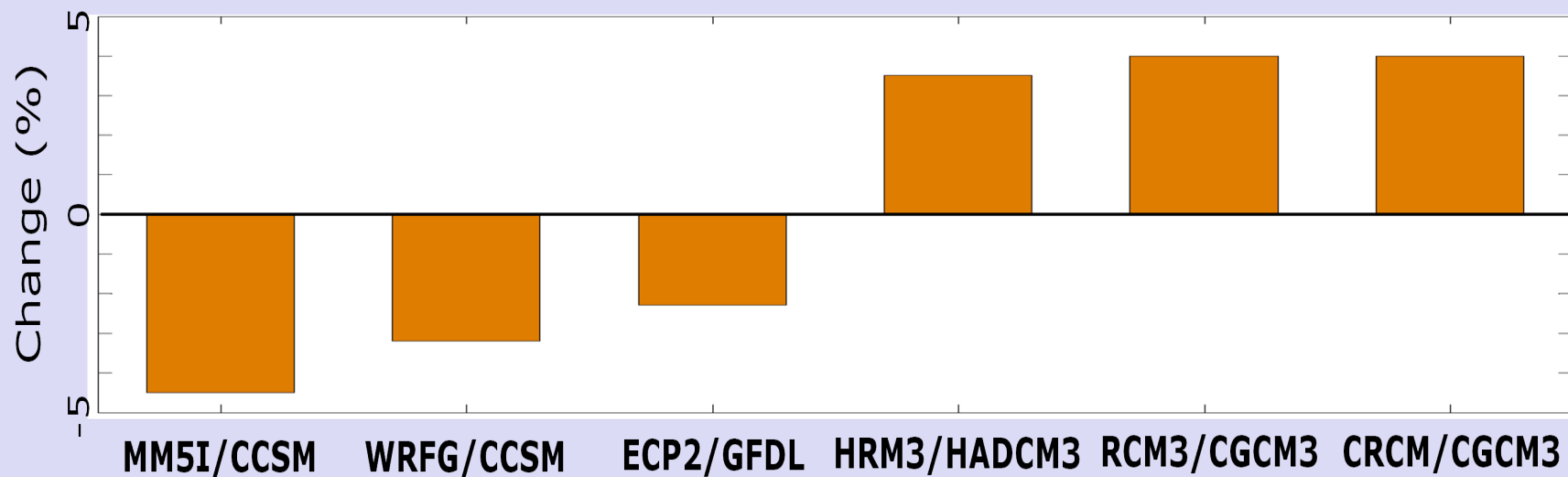
Emissions Scenario:

A2: regionally oriented
and fast economic growth

study region

Recent Evaluation of RCM/GCM over Western U.S.

Models indicate different signs and magnitudes of changes in the mean precipitation over the Western U.S. under the SRES A2 emissions scenario.



Trend of area-average precipitation (comparing 2040-2070 with 1970-2000)

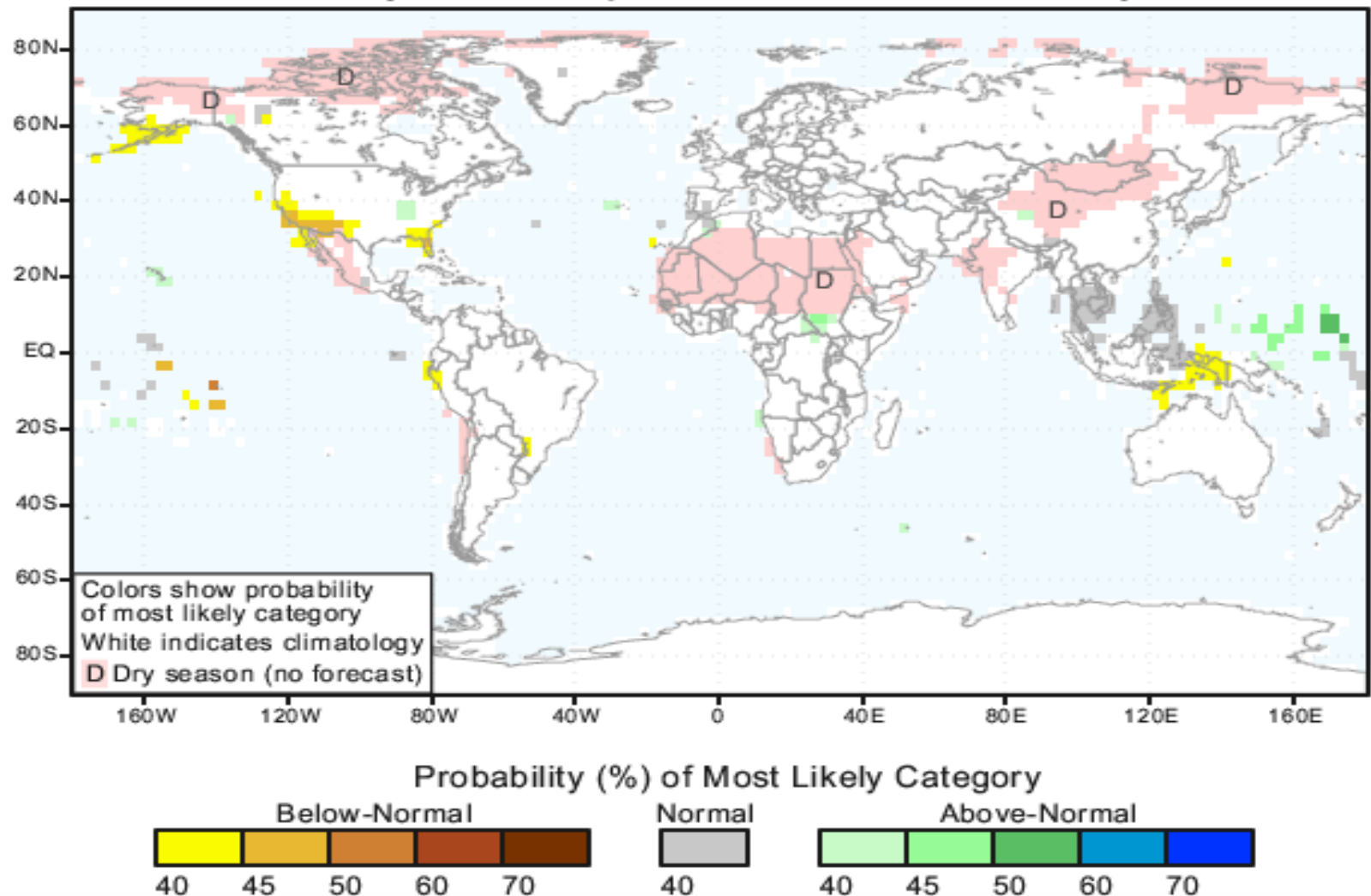


Wei Chu 2011



IRI 3-Month Multi-Model Probability Precipitation Forecast

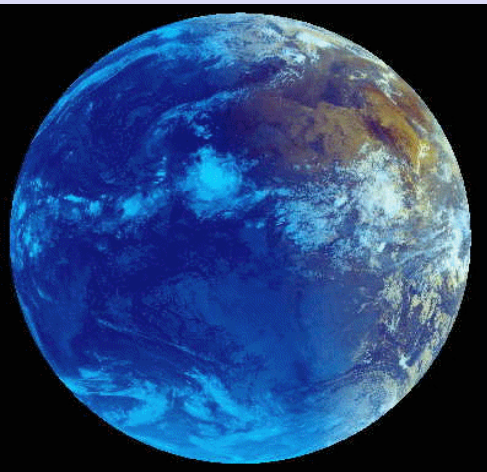
IRI Multi-Model Probability Forecast for Precipitation
for February-March-April 2014, Issued January 2014



Recent Assessment of Seasonal Climate Forecasts

*Quoting from
Science, Vol. 321,
15th August 2008*

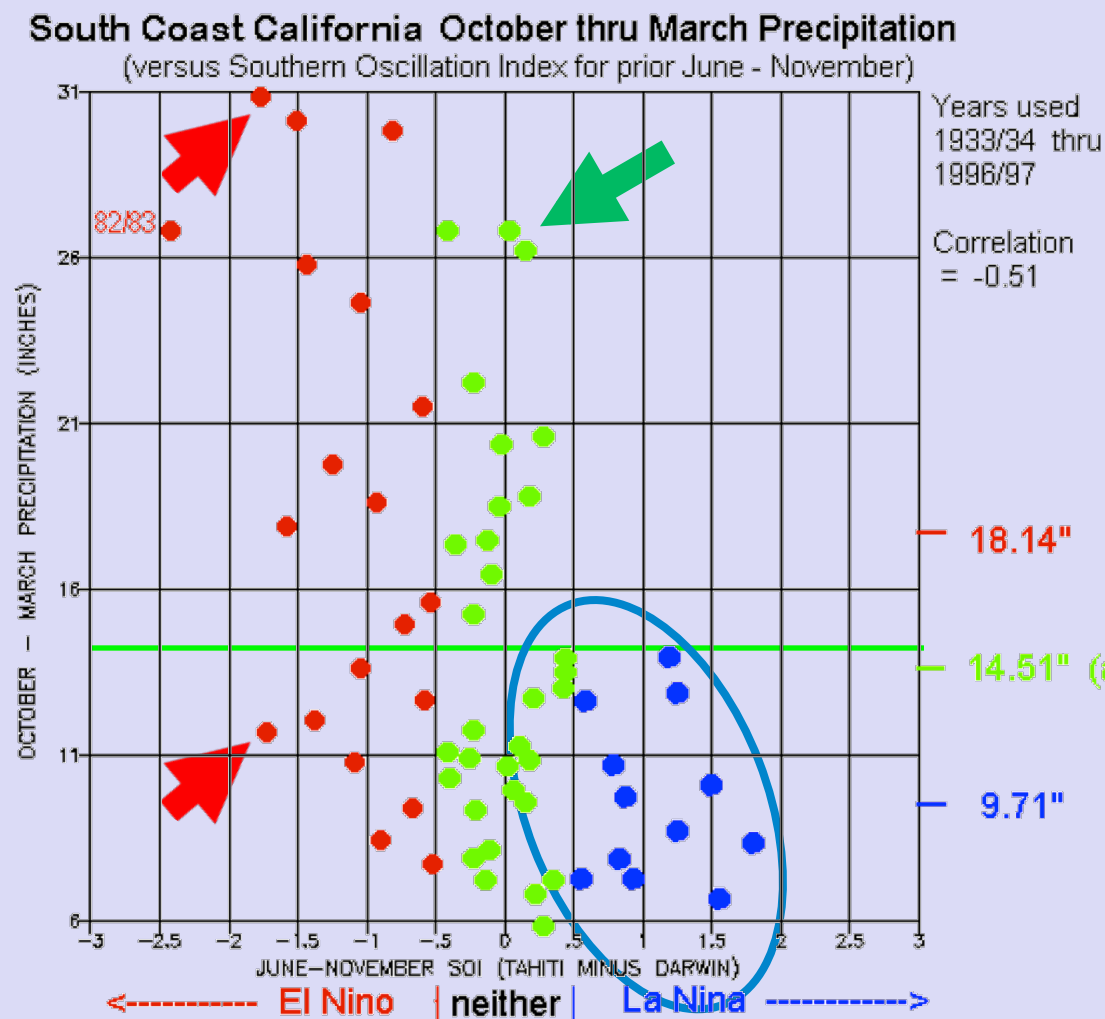
Livezey & Timofeyeva - BAMS, June 2008.



- *“About the only time forecasts had any success predicting precipitation was for winters with an El Nino or a La Nina”*



ENSO Example: South Coast California



**El Nino winters
may be very wet.**

**Very wet winters
are typically El
Nino winters, but
not always...**

**La Nina winters
are typically dry,
but reliably not
wet.**



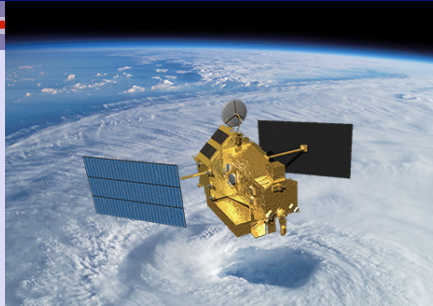
Original idea of scatterplots By: Redmond and Koch 1991

Hydrologically - Relevant Remote Sensing Missions



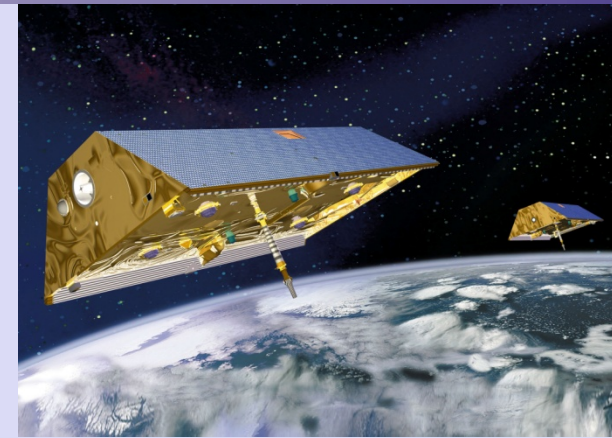
SMOS

ESA's Soil Moisture and Ocean Salinity (2009)



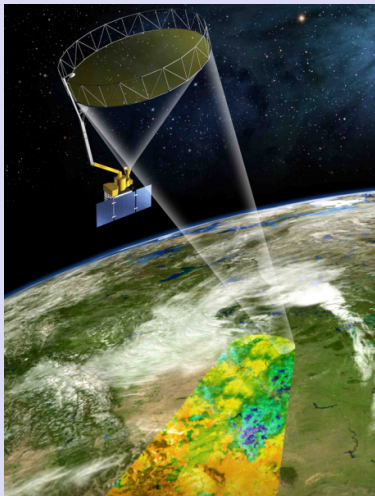
TRMM

The Tropical Rainfall Measuring Mission



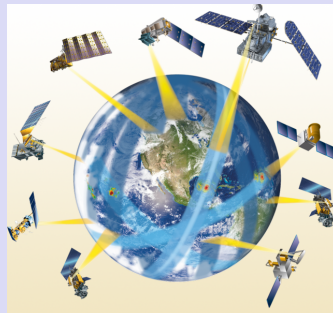
GRACE

Gravity Recovery and Climate Experiment (2002)



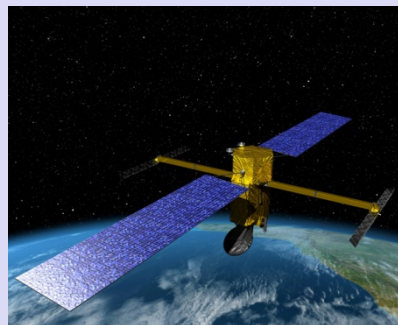
SMAP

Soil Moisture Active Passive Satellite(2014)



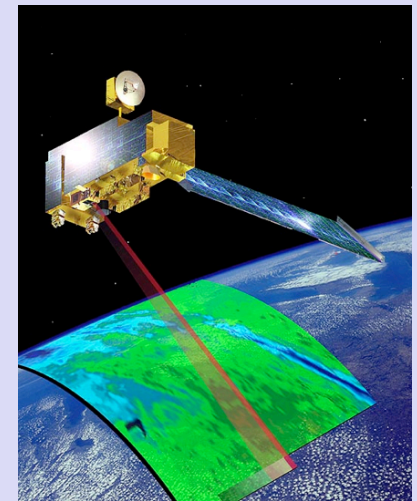
GPM

Global Precipitation Measurements (2014)



SWOT

Surface Water and Ocean Topography (2020)

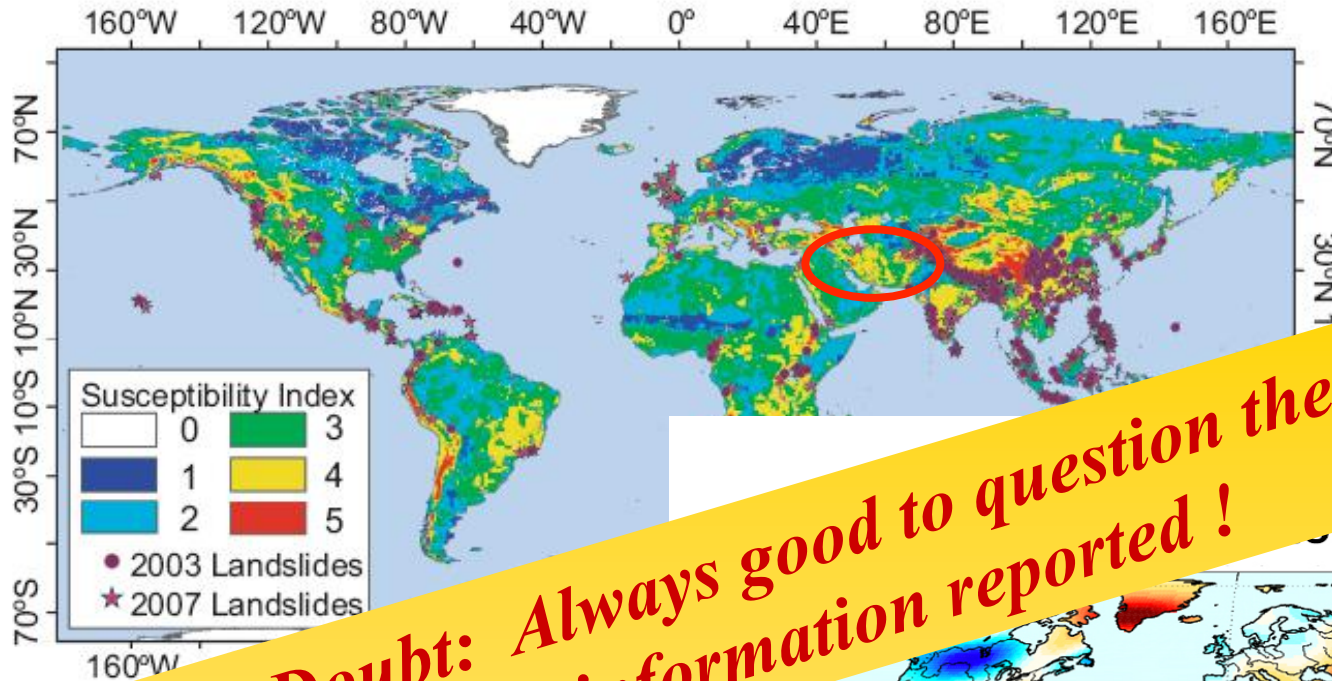


MODIS

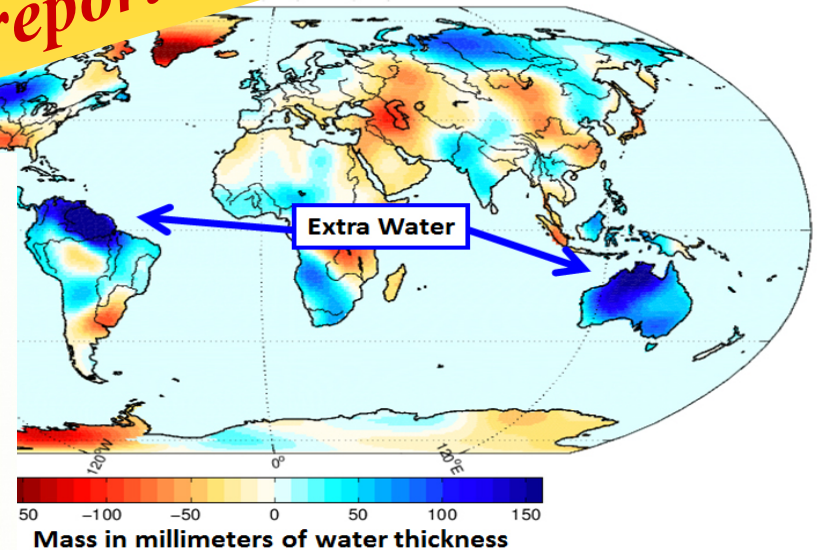
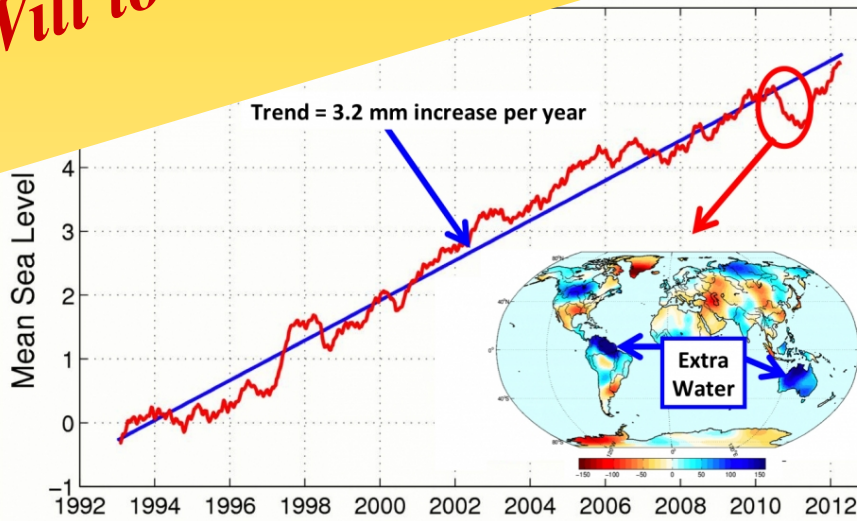
*Moderate Resolution Imaging Spectroradiometer
(1999) , (2002)*



Landslide Risk map:



Will to Doubt: Always good to question the credibility of information reported !



What is the Message?

- *Despite advances to date, predicting the future Hydro-Climate variables will remain a major challenge:*

Future is complex and observing and modeling its future is challenging. So, “have a design and planning is still the safest approach!”

will to do so “generated” by models.

- *Long-term and sustained observation programs are critical, especially for model verification. Without some degree of verifiability, hard to expect their use*



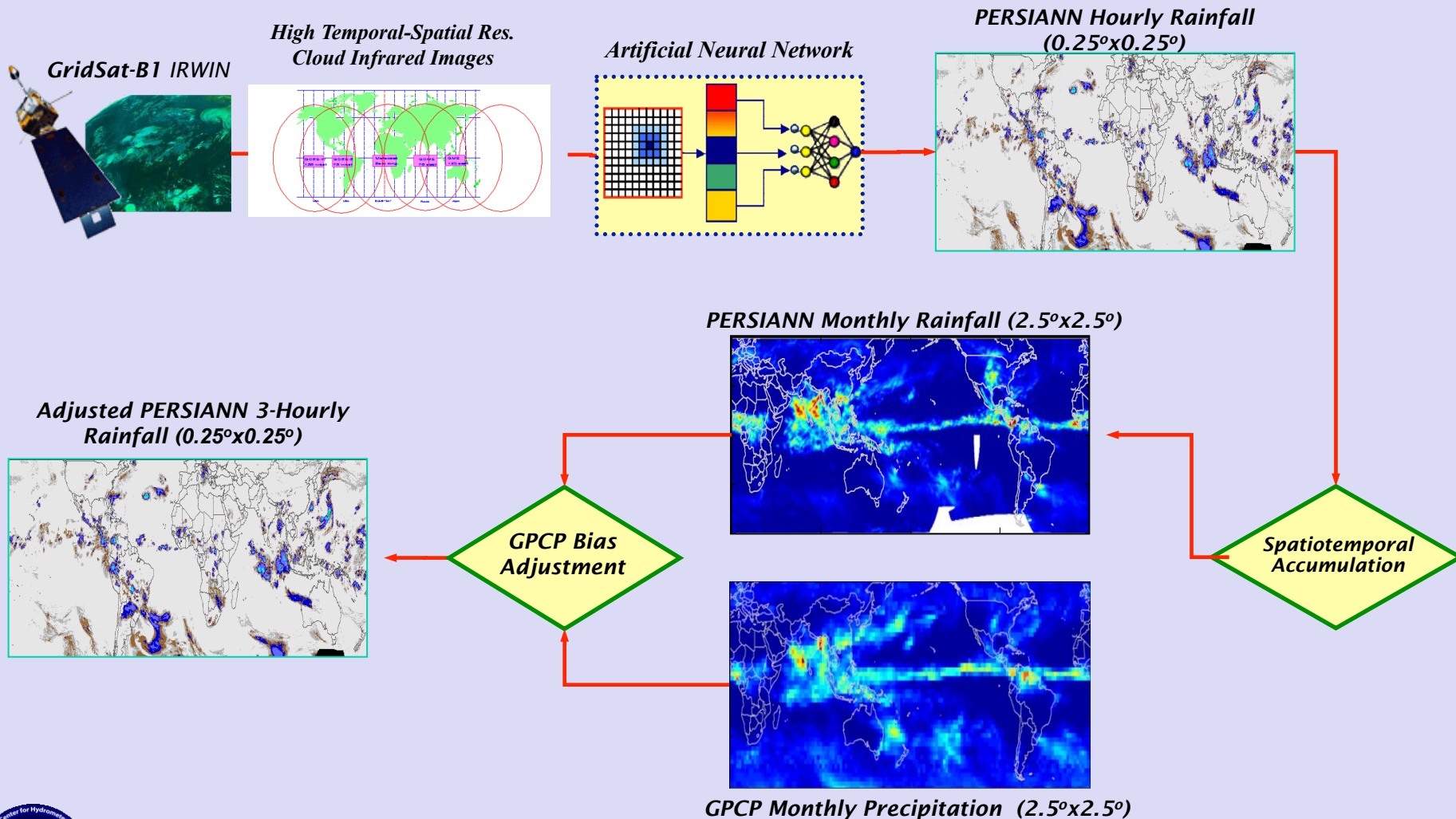
Thank you for the Invitation

08/14/2009

Somewhere in New Mexico, USA - Photo: J. Sorooshian

Back up slides

Bias Adjustment of PERSIANN Estimates



CHRS Web Usage Stats

- **G-WADI interface usage:** http://fire.eng.uci.edu/gwadi_stats.html

Number of Distinct hosts served: 44,067 (Since Jan.1, 2010)

Year	#requests	#pages	Volume (GB)
2010	663,957	116,599	348.39
2011	970,985	203,599	366.51
2012	1,391,260	305,269	390.09
2013 (10/17)	1,664,713	264,864	417.58

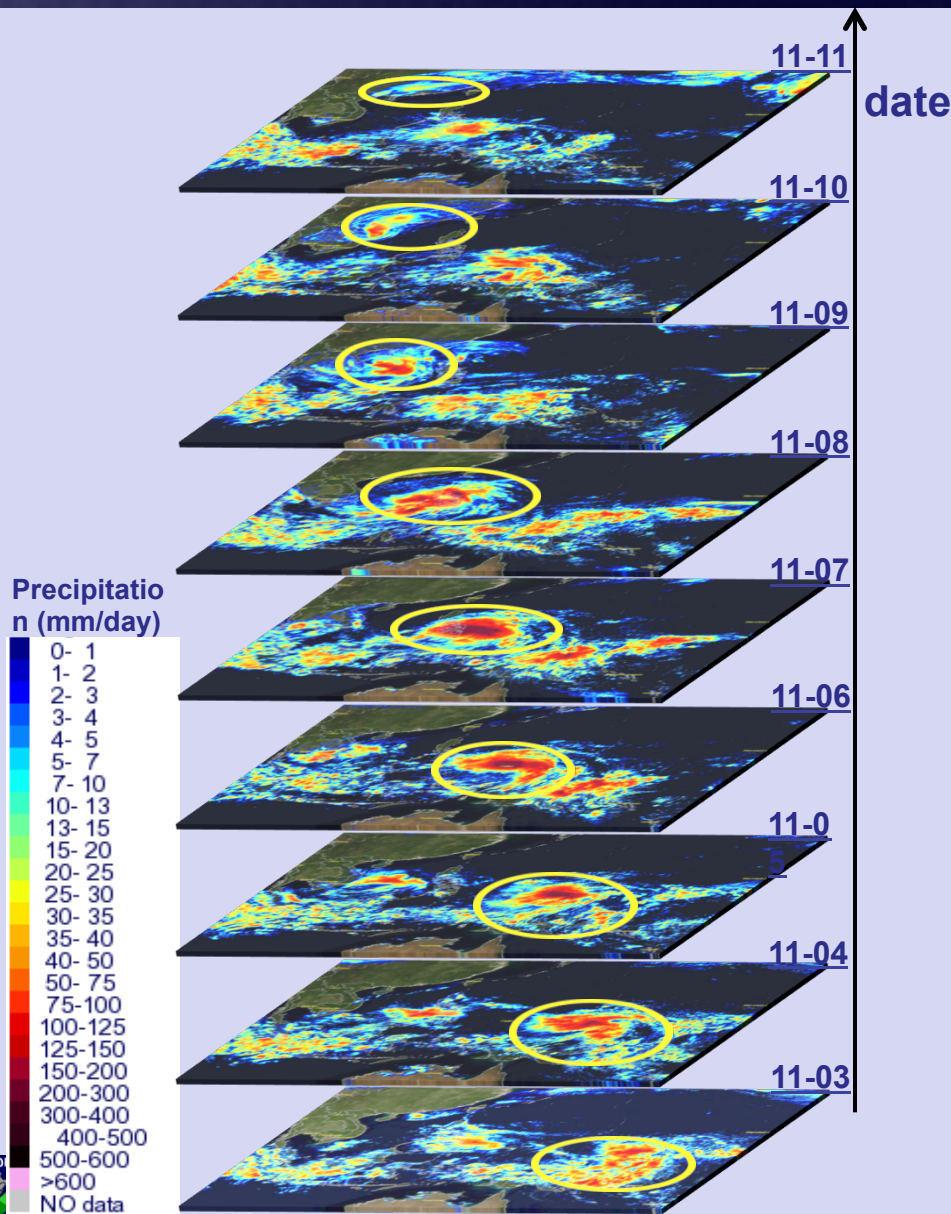
- **HyDIS interface usage:** http://fire.eng.uci.edu/hydis8_stats.html

Number of Distinct hosts served: 13,231 (Since Jan.1, 2010)

Year	#requests	#pages	FTP d/loads
2010	238,771	101,202	835
2011	313,328	201,640	1086
2012	311,953	225,850	1521
2013 (10/17)	137,154	71,056	1585



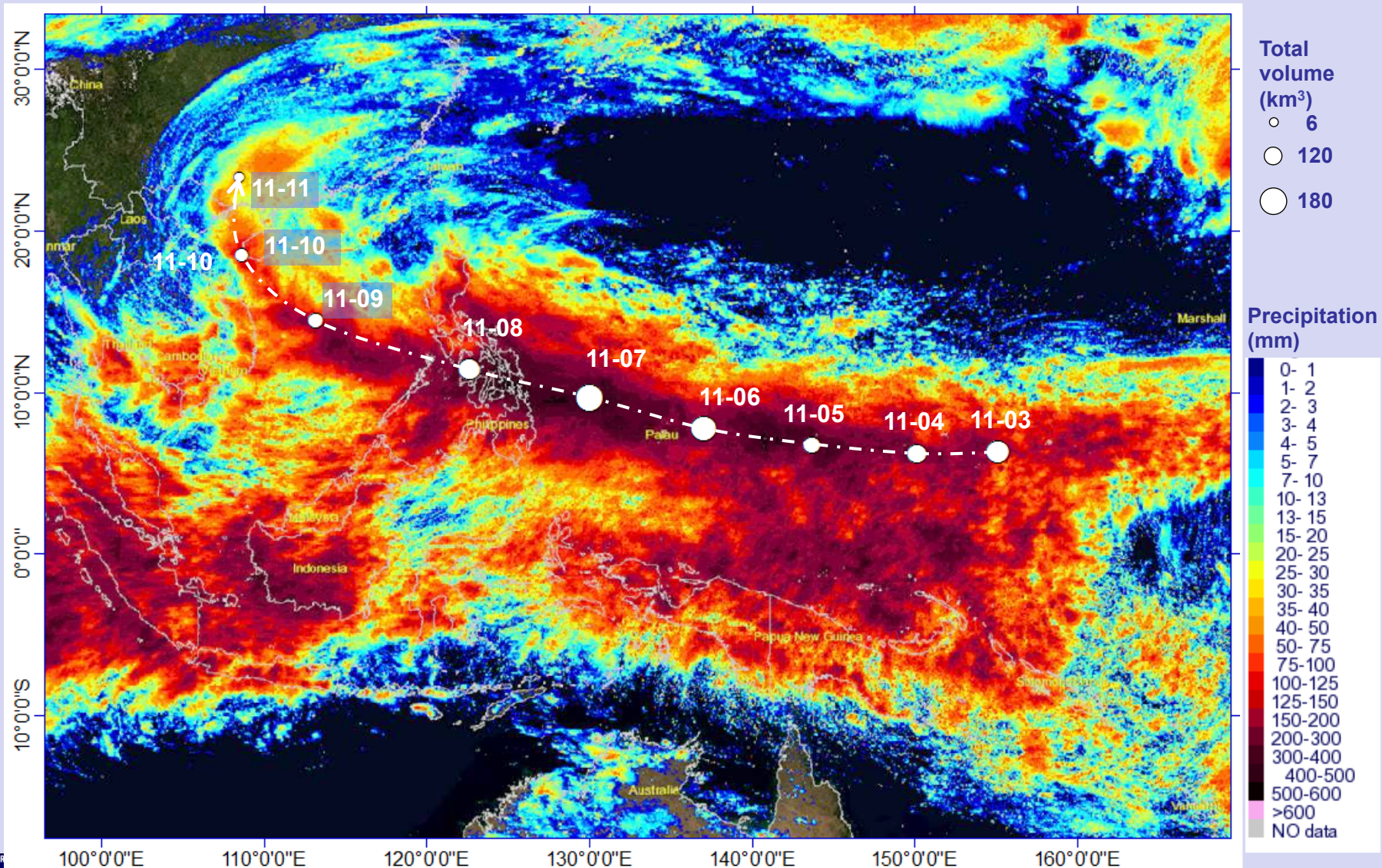
Daily precipitation (mm/day) of Typhoon Haiyan



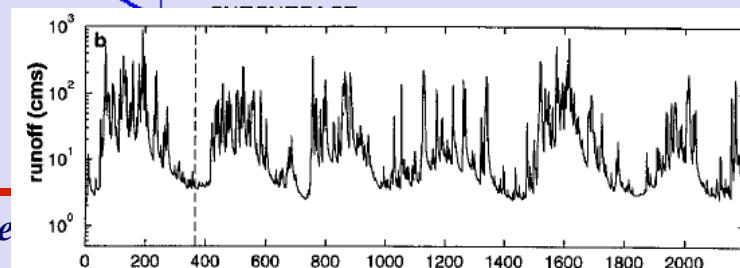
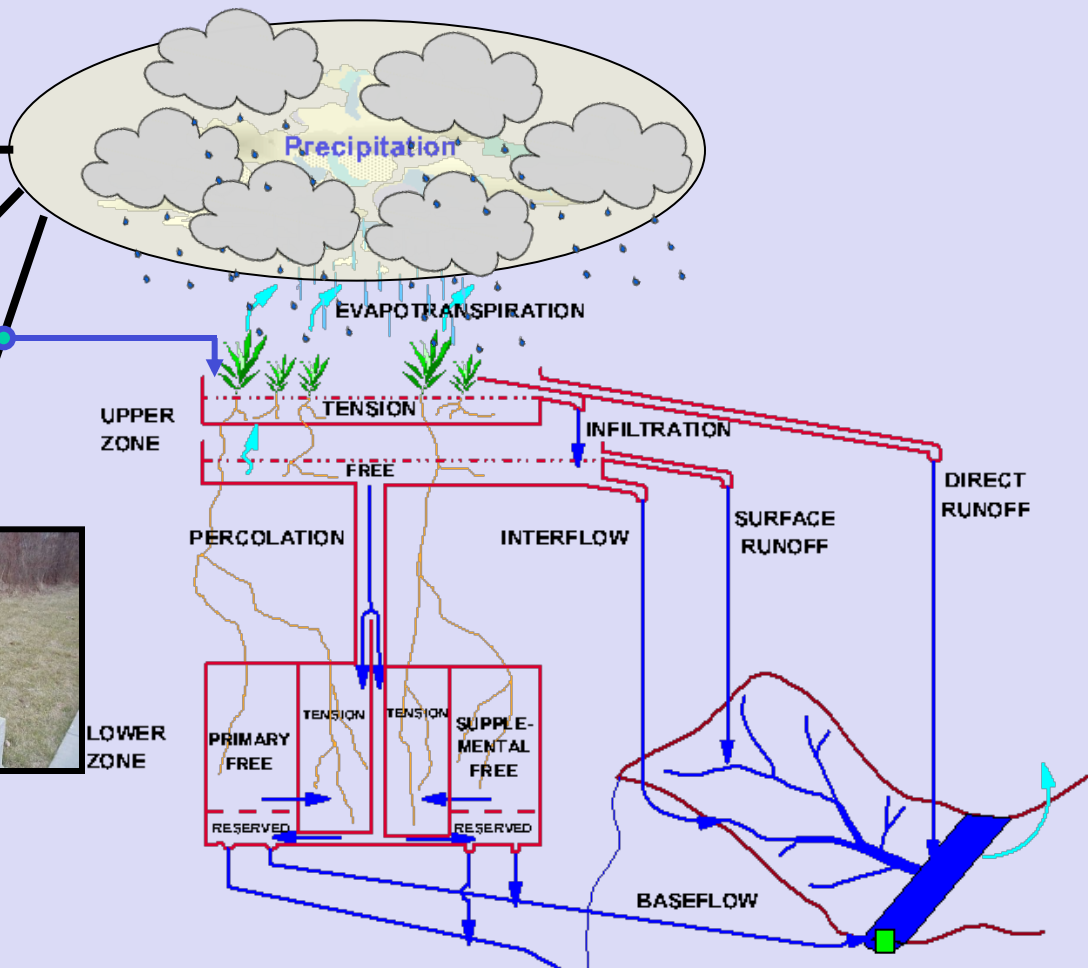
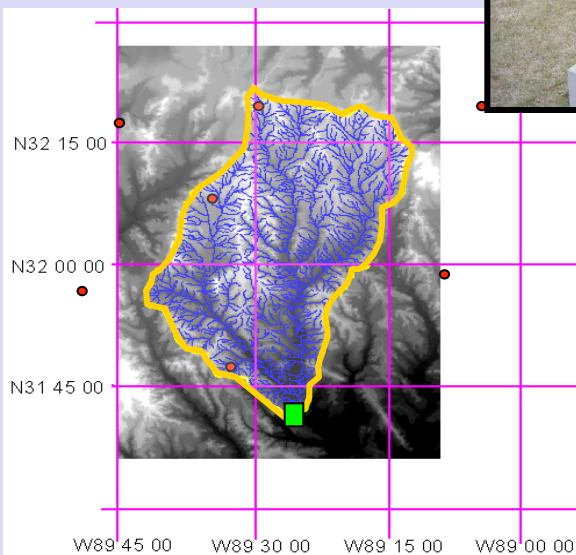
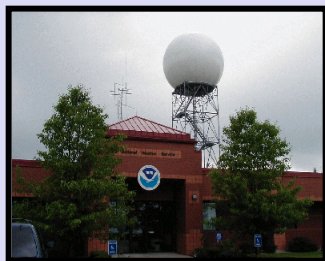
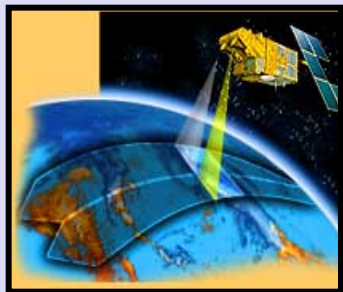
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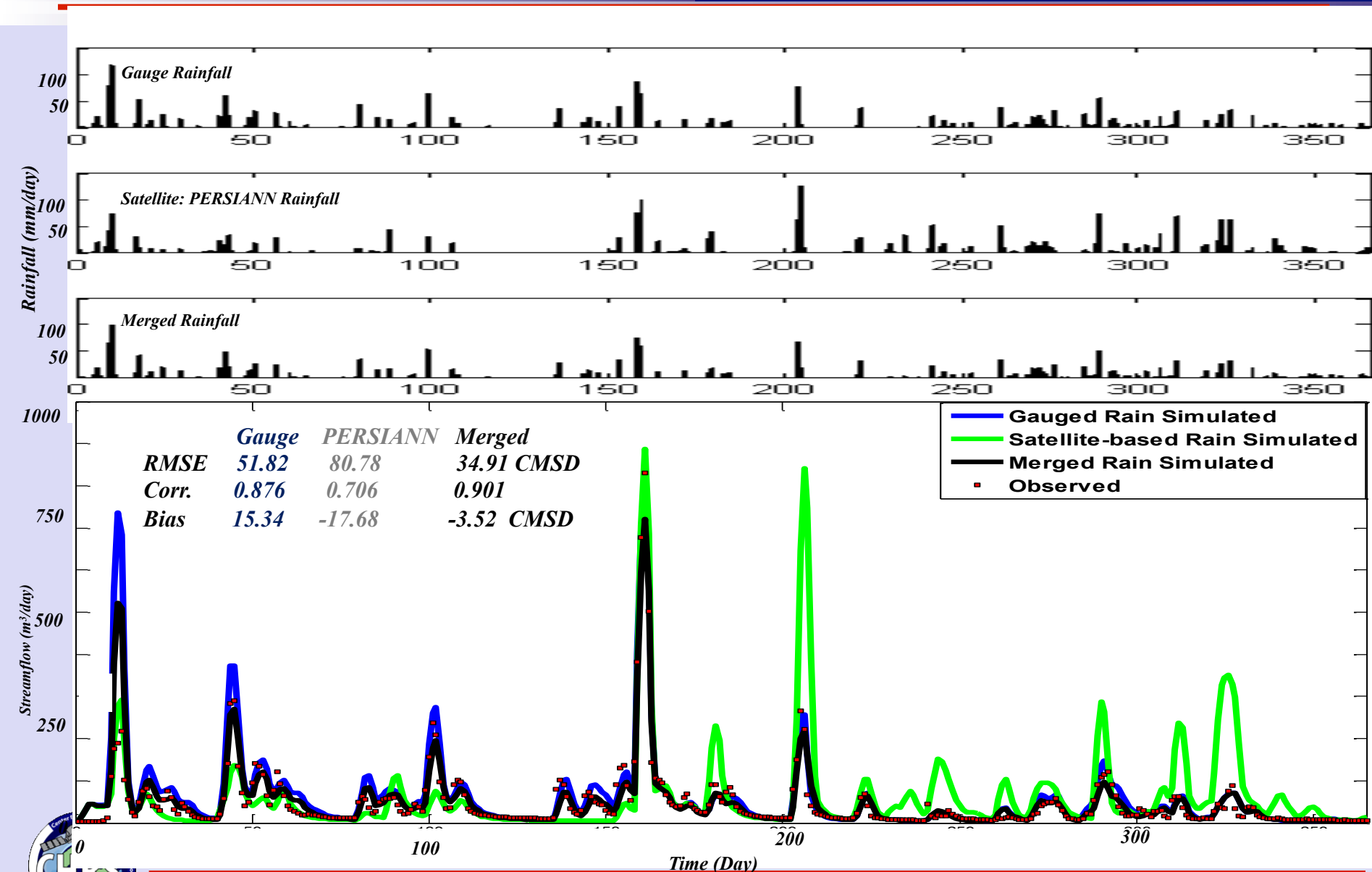
Typhoon Haiyan – Total Accumulated Precipitation (mm)



Basin Scale Precipitation Data Merging



Runoff Forecasting from Gauge, PERSIANN, and Merged Rainfall



Large-Scale Irrigation and Incorporation in Models

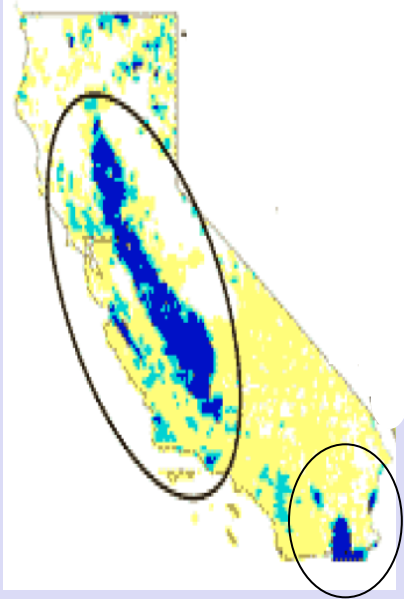


Impact of Irrigation

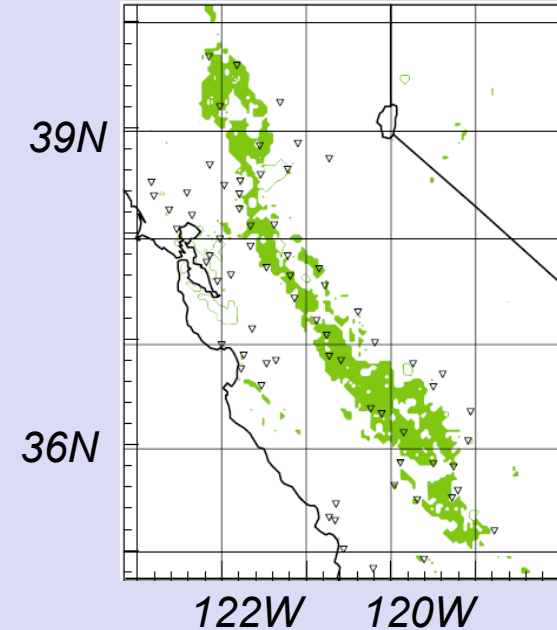


“Observed” vs “Model-Generated” Data

Irrigation areas



CIMIS stations



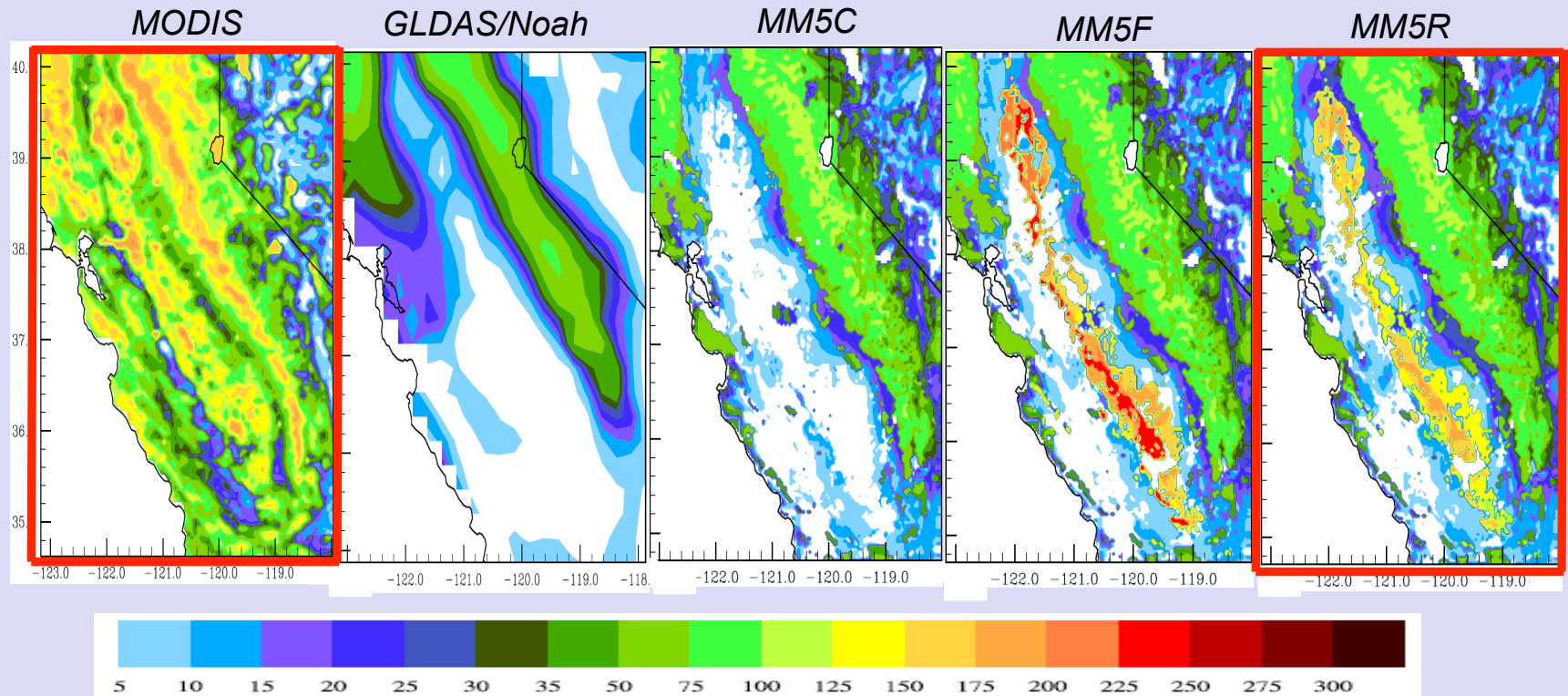
Studies over California's Central Valley Irrigation Region

Sorooshian et al. 2011 & 2012



Center for Hydrometeorology and Remote Sensing, University of California, Irvine

Actual ET comparison-spatial distribution – JJA 2007

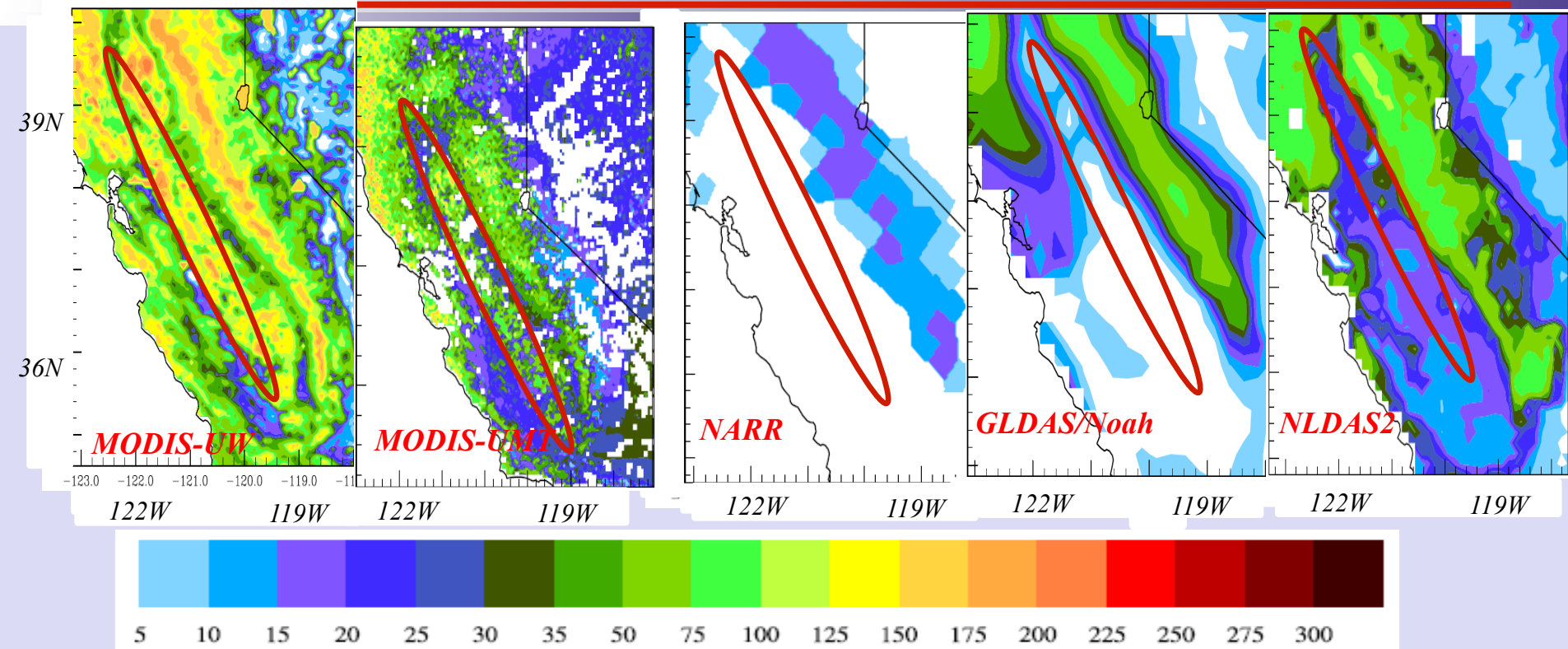


Monthly ET (mm/month)

Results from MM5, with more realistic irrigation scheme, show significant improvement in capturing ET over irrigated Central Valley in California (compared to MODIS - ET estimates). MM5F overestimated.



Actual ET Estimates From Different Data sets– JJA 2007



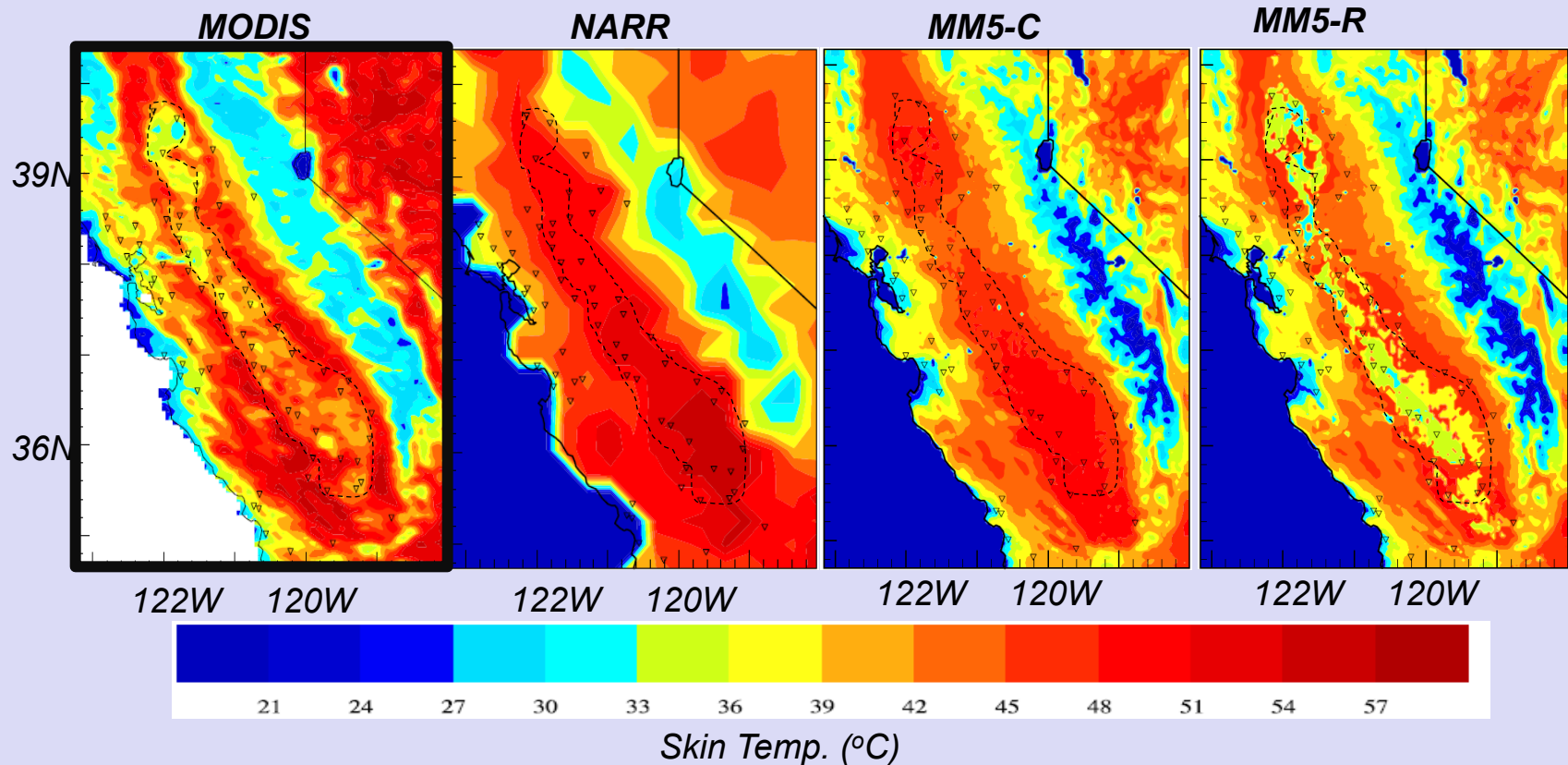
2007 JJA Monthly ET (mm)



Li et al, 2011



Mean skin surface temp. at daytime in June, July and August, 2007.



Adding irrigation into RCM (MM5), Improves the model's ability to simulate, more closely, the temperature patterns observed by MODIS

In a nutshell!

- *ET Underestimation by MM5 control run is roughly about 10 million Ac-Ft of water/yr*
- *ET Overestimation by MM5 with “full-saturation” irrigation is about 6.5 Million Ac-Ft/yr*
- *Use of the realistic irrigation scheme results in only 1.5 Million Ac-Ft/yr of overestimation.*

placed in Societal context :

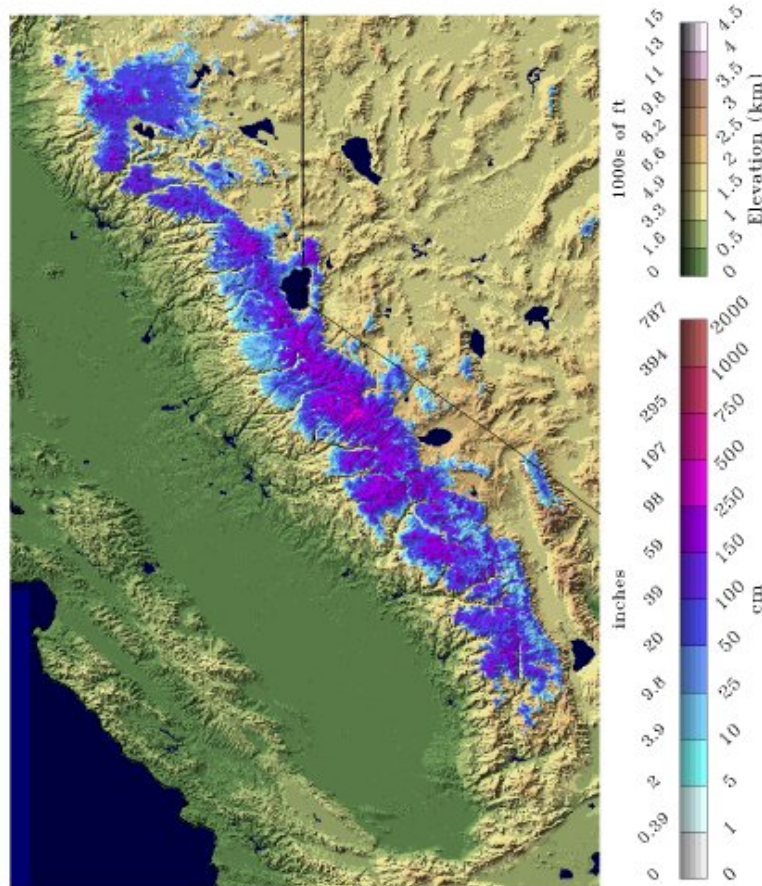
Roughly speaking, the amount of ET underestimation equals supply requirement of 13 million households and the overestimation covers the needs of 9 million households per year.



MODIS Snow Depth(inches) for California

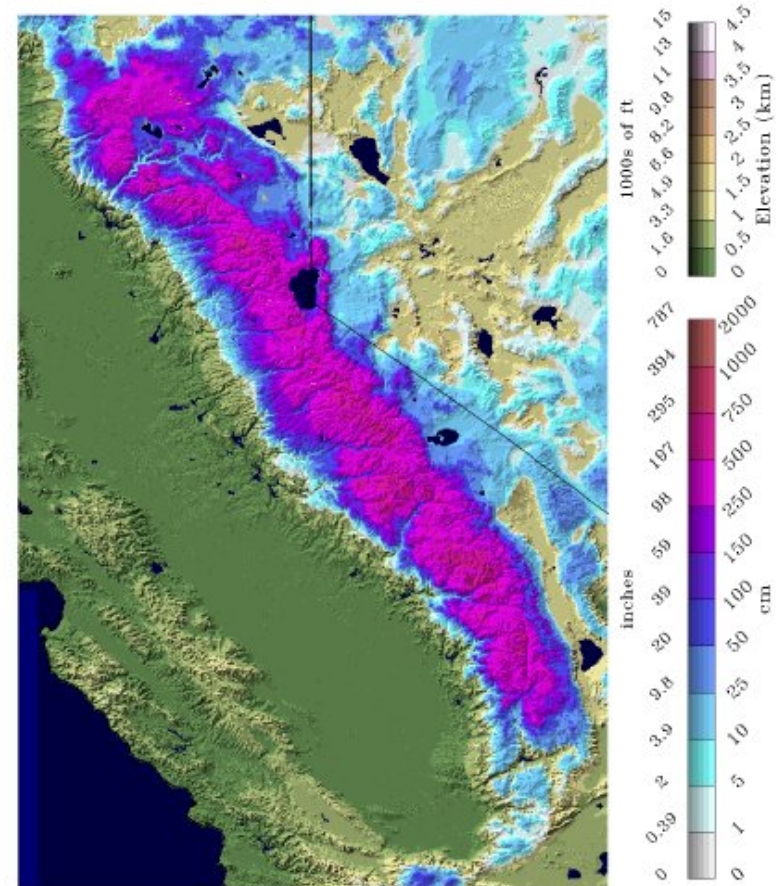
Snow Depth

2013-03-22 06



Snow Depth

2011-03-22 06



NATIONAL SNOW 2012-
ANALYSIS 2013

NATIONAL SNOW 2010-
ANALYSIS 2011

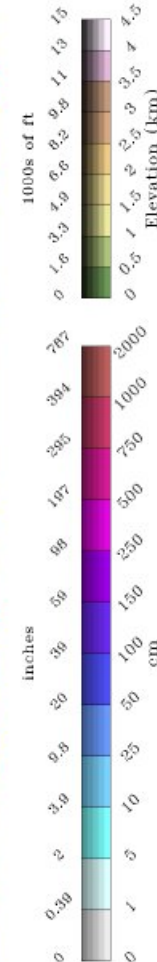
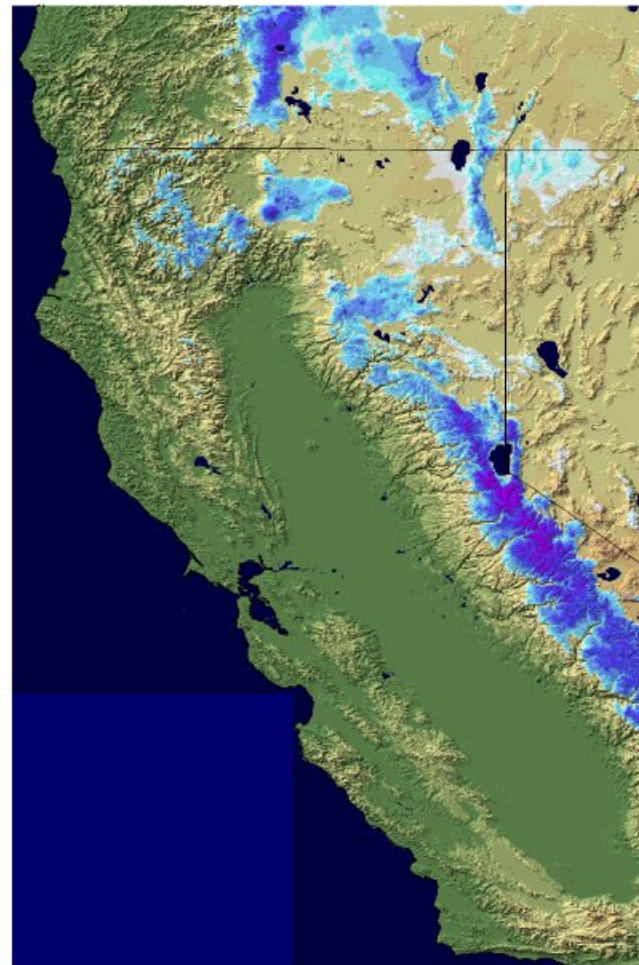
Source: <http://www.nohrsc.noaa.gov>

Center for Hydrometeorology and Remote Sensing, University of California, Irvine

Current Snowpack: After Early February Storm

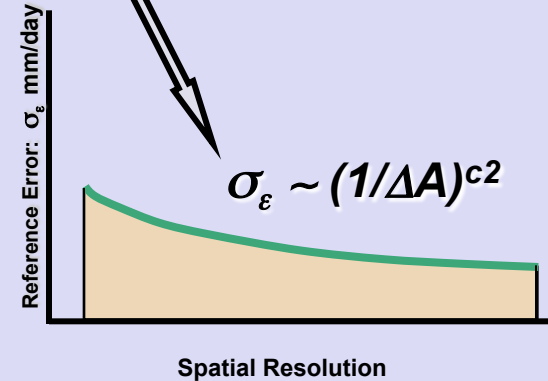
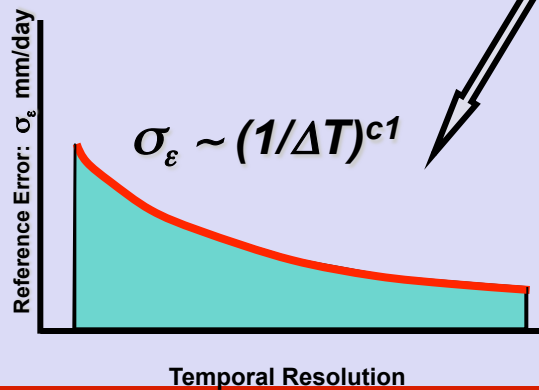
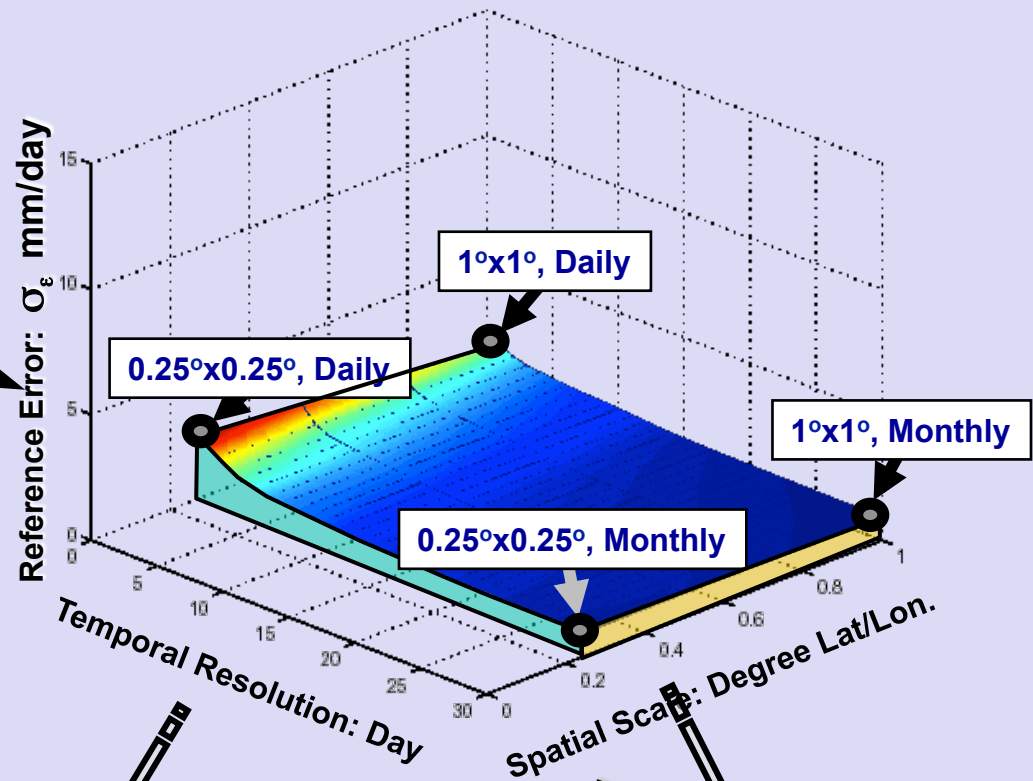
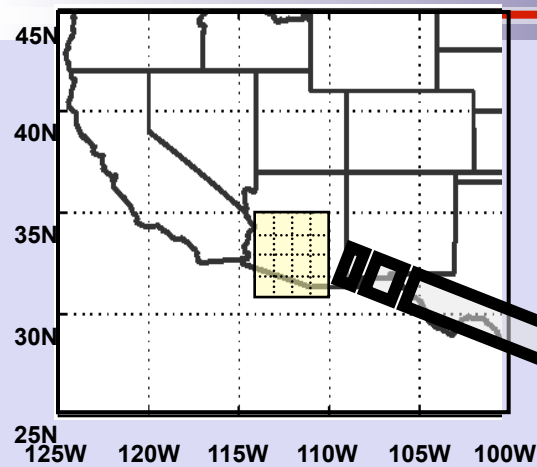
Snow Depth

2014-02-11 06 UTC



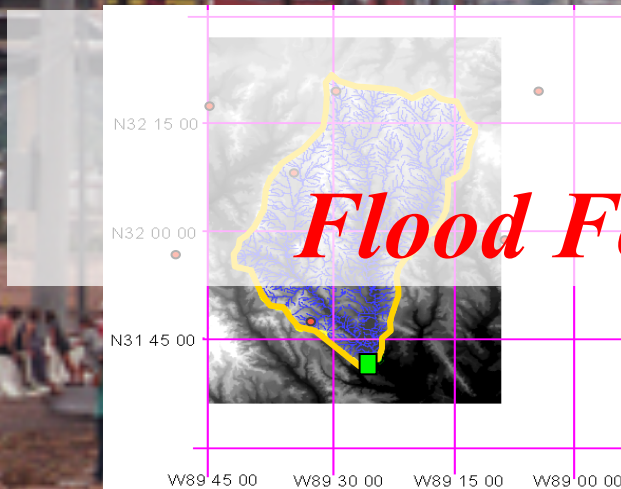
National Snow 2013-2014 Analysis

Spatial-Temporal Property of Reference Error



Satellite Rainfall Estimation for Operational Use

Streamflow forecasting of a catchment in US using UCI-PERSIANN rainfall Estimates for use in the US National Weather Service Runoff Forecasting System (NWSRFS).

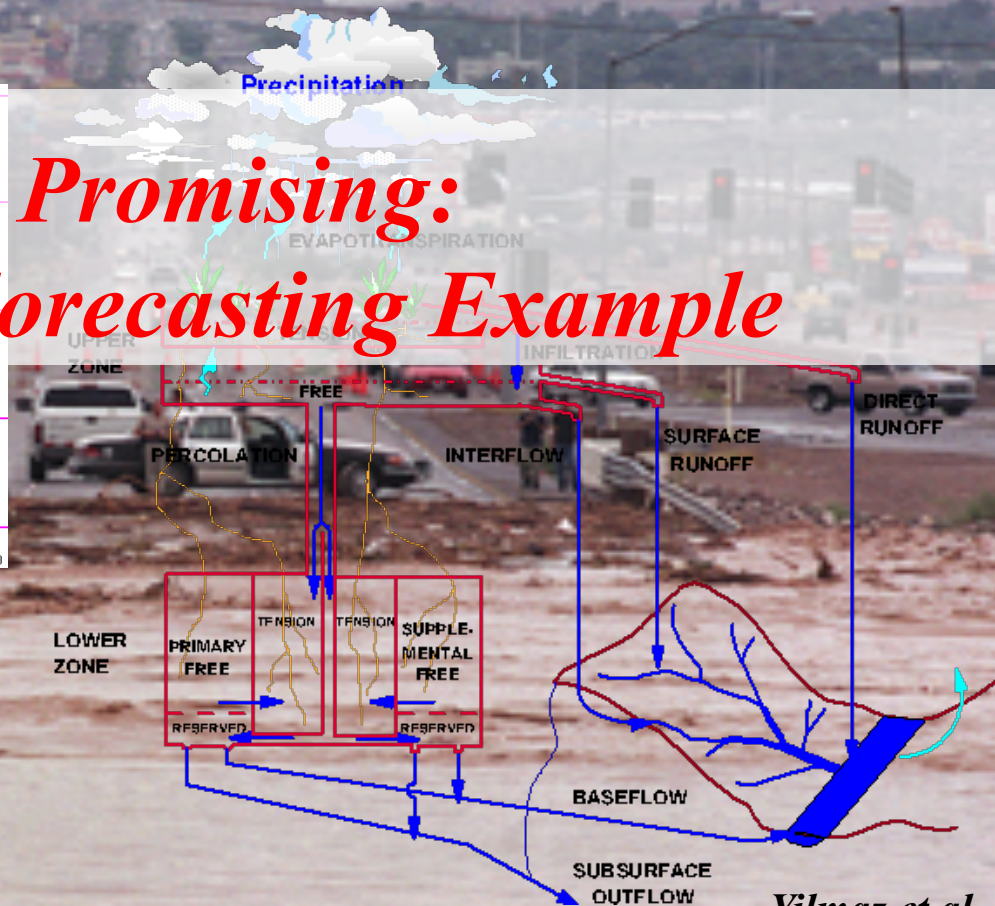


- Gages used by NWS

Leaf River Near Collins
Mississippi
USGS # 02472000

Basin Area : 753 mi²

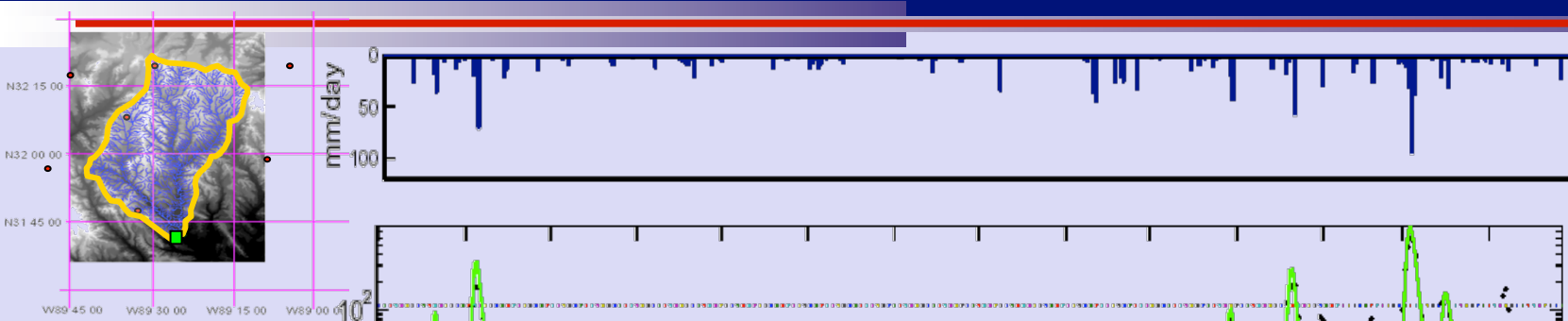
*Promising:
Flood Forecasting Example*



Yilmaz et al. JHM 2005



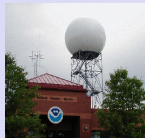
Satellite Rainfall Estimation: Research at UC Irvine



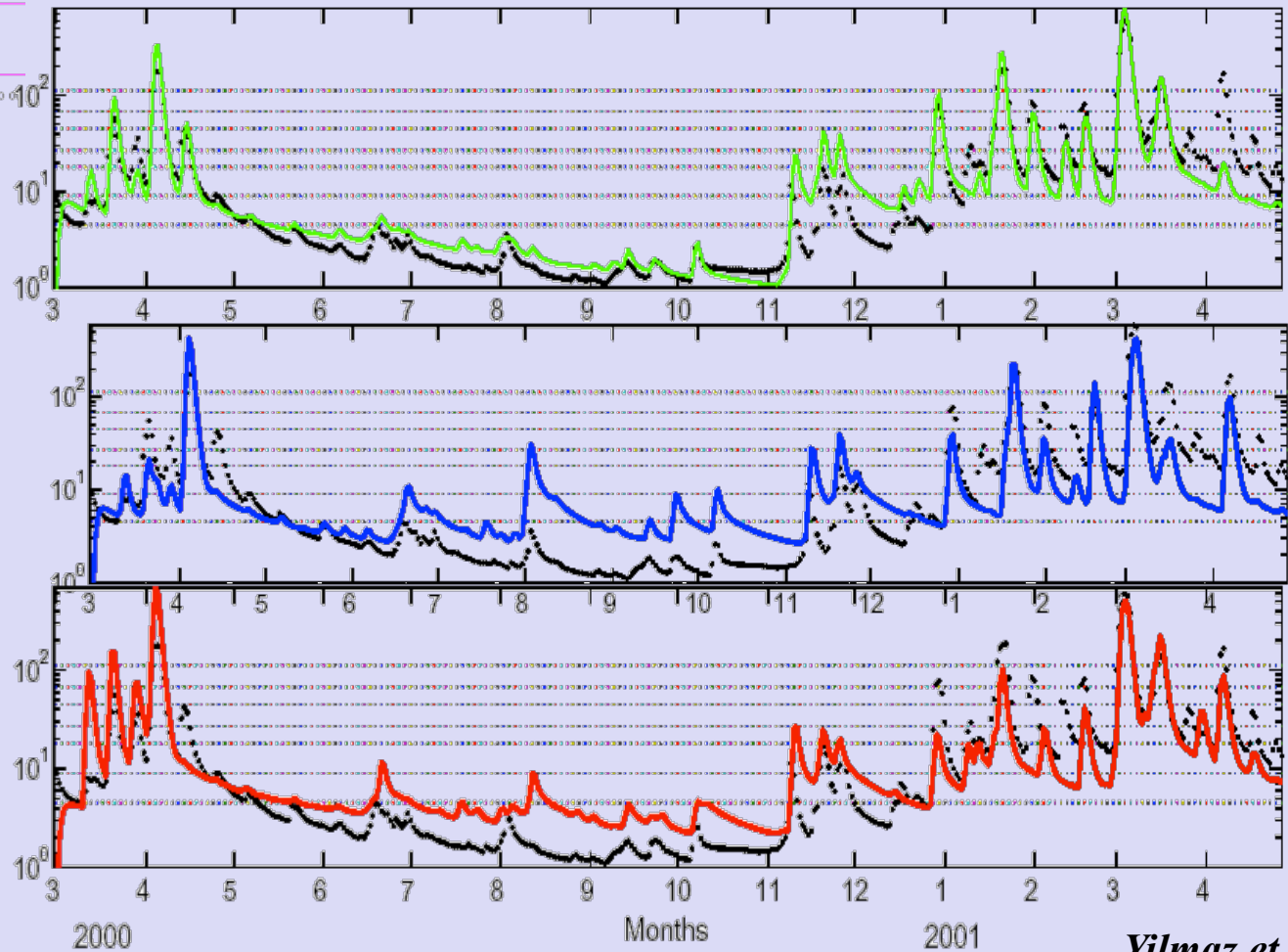
RAINGAGE



RADAR



PERSIANN



Corr =0.95
RMS =23.9
BIAS =-1.32

Corr =0.92
RMS =28.8
BIAS =-6.74

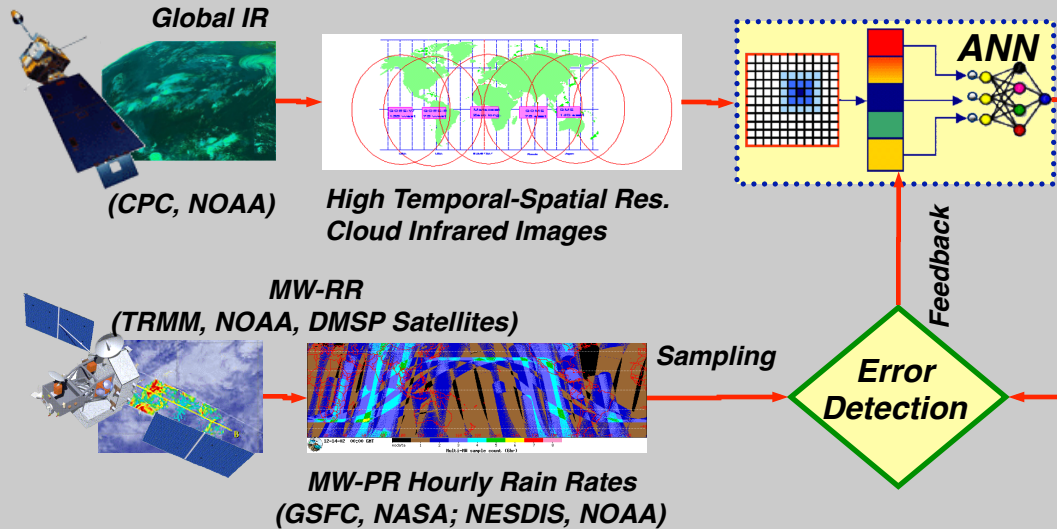
Corr =0.94
RMS =22.6
BIAS =-5.15



Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)

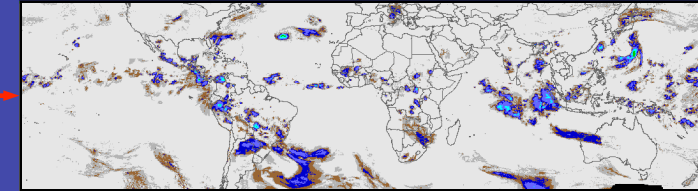
PERSIANN System "Estimation"

Satellite Data



Products

Hourly Global Precipitation Estimates



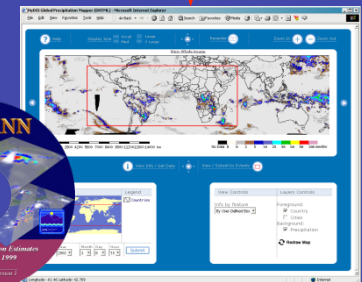
Hourly Rain Estimate

Quality Control

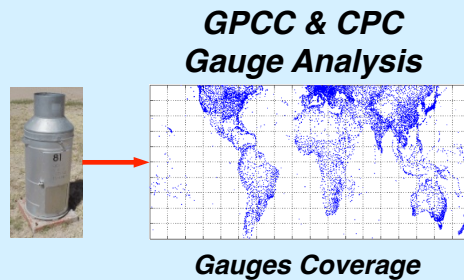
Merging

Merged Products

- Hourly rainfall
- 6 hourly rainfall
- Daily rainfall
- Monthly rainfall



Ground Observations



Center for Hydrometeorology and Remote Sensing, University of California, Irvine